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The true activity levels of Norwegian actively managed equity mutual funds

- ***An empirical answer to the medias' critique of the actively managed fund industry***

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Abstract

By applying a wide range of activity measures and performance tests, both in a static risk scenario and a time-varying risk scenario, on a sample consisting of 38 actively managed Norwegian equity mutual funds, this quantitative study aims to answer the recent debate that has roared the Norwegian media. The actively managed fund industry has been criticized for not being active enough and delivering an inferior product to what the investors are paying for.

By applying Cremers and Petajisto's active share measure in combination with the tracking error, this study elucidates if closet-index funds are a prominent issue in the Norwegian market. Unfortunately, the overall findings are disappointing; approximately 60% of the funds in the sample are classified as closet-indexing. That is, more than half of the available actively managed equity mutual funds in Norway are in fact trailing a benchmark index, and thus delivering a highly passive product.

In addition, the 38 funds' performance is analyzed in the period from 1 January 2006 to 31 December 2015 by applying a set of performance tests derived directly from the CAPM framework. By applying the traditional Jensen's alpha regression for micro forecasting abilities, and the Treynor & Mazuy market timing model for macro forecasting abilities, I am able to compare activity levels and performance, along with managerial abilities. In addition to the traditional performance tests, this study follows Ferson & Schadt's approach of analyzing performance in a time-varying risk scenario, in order to portray a more realistic picture of the risk levels and help mitigate omitted variable bias. However, I find no evidence of a relationship between activity levels and performance or between activity level and managerial abilities. In fact, I identify an inverse relationship between activity levels and performance. The least active funds perform better on average than the more active funds. Moreover, there are more evidence of superior forecasting abilities among the least active funds than the more active funds, which is exactly opposite of what you would expect, taking into account that active fund management is resource intensive, and thus a pricy product.

Ultimately, the activity levels are compared to the funds' TER, in order to elucidate whether the relationship between activity levels and costs are according to theory. Yet again, this study provides disappointing results from the actively managed fund industry's point of view, as there seems to be an irrational relationship between activity levels and costs. According to the findings in this study, the investors investing in actively managed Norwegian equity mutual funds are actually overpaying for the product and performance they receive, which supports the critics' accusations.

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1.0 Introduction

1.1 Background

The debate on whether actively managed funds truly are preferable over passively managed funds or not has been on financial scholars' minds since the introduction of the CAPM framework in the 1960s. Numerous studies have been performed on active funds' performance, and the researchers are yet to come up with an unambiguous answer on the aging "active vs passive fund" discussion. However, recently there has been a shift in the focus on actively managed funds from their performance towards the actual activity levels within the funds. Are the funds as active as they claim to be?

On June 21st 2016, a groundbreaking event in relation to actively managed mutual funds took place in Norway; the Norwegian government filed a lawsuit on behalf of 150 000 private investors against the largest retail bank in the country[1]. The government claimed the bank was fraudulently charging fees for one of their actively managed equity mutual funds, when they in fact delivered a passive product. According to their research, the retail bank's fees were too high relative to the risk the fund was taking, and the investors were severely overpaying for the product they received. In fact, the government calculated the overpayments to reach a sum in excess of 690 MNOK for this particular fund. This is the first time in history a government was taking legal actions against an actively managed mutual fund in order to defend the investors' rights, and in the wake of the lawsuit they might pave the way for a global change in the perception of the actively managed fund industry. For instance, in the aftermath of the Norwegian government's lawsuit, Sweden and Denmark have intensified their monitoring of domestic actively managed mutual funds, suspecting them of delivering an inferior product than what the investors are paying for.

The quarrel on activity levels within funds eventually reached the media's attention, and has since dominated the financial news in Norway. Traditionally, actively managed funds have been a popular investment vehicle in Norway, and especially in terms of pension savings. After the media started questioning the funds' motive, claiming they were driven by greed, overcharging for inferior investment products and taking advantage of uninformed investors, the funds have been forced to publicly defend their case. The funds point to the fact that they have delivered good returns on their products, and that they actively analyze the market in order to identify the best securities. The government, on the other hand, dismisses these statements, claiming that the investors have paid for a product they did not receive.

[1] https://www.nrk.no/norge/forbrukerradet-med-gigantsoksmal-mot-dnb-1.12999016 - downloaded 25.09.16

They say a computer replicating the benchmark index could have produced the same returns as the fund, at a fraction of the cost.

Based on the public conflict between Norway's largest retail bank and the Norwegian government, I have decided to investigate this matter further by performing an empirical study on the true activity levels of actively managed mutual fund in the Norwegian market. Throughout the study, I aim to answer whether the Norwegian media and government are righteous in their critique of the industry. Moreover, I will investigate whether self-proclaimed actively managed funds delivering a passive product is a widespread issue in the Norwegian market. By comparing activity levels on an individual fund level with the funds' expenses, performance and managerial abilities, I aim to create a comprehensive study that elucidates several aspects of the Norwegian funds' activity levels.

1.2 Problem Statement

The main focus-point of this study is to elucidate and provide empirical findings to the ongoing debate about activity levels in Norwegian actively managed mutual funds. Hence, the main problem statement is as follows:

- Is the Norwegian government and media's critique of the actively managed equity mutual fund industry fair given their true activity level and performance?

In order to answer the main problem statement, I will also be answering the following sub-questions:

- Are closet index funds prominent in the Norwegian market?
- Do the activity levels of actively managed Norwegian equity mutual funds coincide with their costs and performance?
- Are the most active funds better at micro and macro forecasting?
- Are investors overpaying for active fund management in the Norwegian market?

1.3 My contribution

Studies have been performed on activity levels in some financial markets for some time, such as Cremers & Petajisto's (2009) study on the U.S. market and Vestergaard's (2013) study on the Danish market. However, the academic literature on the true activity levels of actively managed mutual funds in Norway is scarce as it just recently caught the public's attention. The only major contribution, to my knowledge, came in form of Norstein & Varran's study from 2015. However, Norstein & Varran performed a comprehensive study on the Norwegian market, and thus had broad focus on their study. Hence, they only analyzed the issue of true activity levels within Norwegian actively managed mutual funds at an aggregate level. My study will be a significant contribution to the area of research Norstein & Varran started in 2015 and will complement their findings.

Unlike previous studies, this study analyzes activity levels on an individual funds basis, in addition to aggregate levels. Moreover, the activity levels are compared to evidence of managerial abilities in order to detect a potential relationship between activity levels and managerial skill. The most significant contribution comes in the form of identifying the amount of closet indexing funds present in the Norwegian market, which, as explained in section 1.1, is a highly tabloid topic. Ultimately, the study looks at the relationship between individual fund activity and the Total Expense Ratio, along with the individual funds' performance in order to detect whether investors looking to invest in Norwegian actively managed mutual funds are facing a risk of overpaying for the product they receive.

1.4 Delimitations

There are numerous funds available to investors with different investment strategies, target markets, risk levels etc. In order to obtain a representative sample of funds, to which I aim to apply a range of financial tests and models, a set of selection criteria are introduced. Ultimately, the selection criteria narrowed down the available funds to a final sample consisting of 38 Norwegian actively managed equity mutual funds with a domestic investment mandate and full portfolio disclosure. In order to be classified as a fund with domestic mandate, a minimum of 80% of the assets needs to be invested in domestic securities listed on the domestic stock exchange. Hence, I am only looking at a minor fraction of the total number of available funds in Norway. However, a smaller data sample is preferred because of the increased comparability it provides. Moreover, the results are more reliable and can be applied by any investor looking to invest in a Norwegian actively managed equity mutual fund.

Equity mutual funds have been selected over other types of funds due to the importance of having a suitable benchmark index for the single-index model regressions. Having a suitable benchmark is imperative in order to obtain reliable regression outputs with high explanatory power. Furthermore, a minimum lifespan of three years among the funds in the final data sample were required to make sure I have enough observations to make justified conclusions based on the results from the tests applied.

The performance tests included in this study only covers the period from January 1st 2006 – December 31st 2015. A natural consequence of the ten-year period is that I am only able to measure performance in a limited period of time. However, compared to previous studies on the field, a ten-year period is considered sufficient to obtain applicable results. Moreover, in terms of the activity measures, only the activity levels on December 31st 2015 are measured due to time constraints.

In order to modernize the traditional performance models, I have adopted Skålebråten's (2013) approach of including time-varying risk levels on Norwegian funds. By including a predetermined set of publicly available information variables, based on Ferson & Schadt (1996), the approach portrays a more realistic picture of the funds' performance. Moreover, the time-varying risk levels might improve the explanatory power of the traditional performance models.

In order to measure the activity levels within each fund, Cremers & Petajisto's (2009) "*active share*" method is applied together with the traditional "*tracking error volatility*". The active share method only looks at differences in portfolio holdings between a given fund and the benchmark portfolio, and thus effectively ignores other activity factors. Hence, the strict definition of activity might lead to me wrongfully discarding a fund as passive, by overlooking other activity factors such as trading frequency. However, the active share is a highly appraised method, and is gaining a lot of traction within the financial world as the single-most important measure of activity.

1.5 Structure of thesis

This study is organized as follows; section 2 provides an overview and discussion of the relevant theory applied in this study. In section 3, the data collection and methodology is presented and discussed, while the characteristics and operations of the Norwegian actively managed equity mutual fund industry, along with human behavior and rationale behind fund investments is presented in section 4. Section 5 presents the empirical findings from the financial models applied, while the empirical findings is analyzed and discussed from a practical point of view in section 6. Ultimately, the analyses are summarized and the problem statement answered in the conclusion in section 7.

2.0 Theory

This section provides an overview over the relevant theory applied in this study. It includes both the theoretical foundation of the study and the financial models that have been applied. In addition, previous results from research on the Norwegian market are briefly discussed in order to create some expectations to my results. They are also included to create a basis for comparing my results to earlier studies.

2.1 Measure activity levels of funds

Until very recently, measuring the true activity levels of funds was impossible. An industry-wide definition of an active fund was none existent, and the definition varied from whomever you asked. Some fund managers defined activity levels based on trading frequency, while others defined it based on risk-levels. Consequently, for decades it was close to impossible for governments to monitor actively managed funds, because the fund managers could hide behind a curtain of imprecise definitions in order to claim high activity levels and charge high fees. Luckily, a quantifiable measure of activity has been developed in recent years. Cremers & Petajisto proposed the "*Active Share*" measure in 2009, which finally made it possible to put a definite number on a fund's activity level. This measure is of special importance in this study, where I seek to confirm or disprove the mass medias' and the government's sharp criticism of actively managed funds' activity levels.

2.1.1 Tracking Error Volatility

According to Cremers & Petajisto, the "*tracking error volatility*", or simply *tracking error*, was the traditional measure of activity levels within funds. It is a measure of risk-levels within a fund, and "represents the volatility of the difference between a portfolio return and its benchmark index return" (Cremers & Petajisto, 2009, p. 1). The tracking error is given as:

$$Tracking\ Error = Std.Dev[r_{fund(t)} - r_{index(t)}]$$

An obvious goal for a fund manager will be to achieve a higher return than the relevant benchmark index, while at the same time maintain a low tracking error. A low tracking error minimizes the fund's risk-levels, and thus minimizes the risk of underperforming relative to the benchmark index (Cremers & Petajisto, 2009, p. 6). A high tracking error indicates an active fund, while a low tracking error indicates a passive fund, because a high risk-level implies that the fund manager is differentiating his portfolio holdings from the benchmark index.

Despite previously being a preferred measure of activity levels, the tracking error is being criticized for being too imprecise. First of all, it is difficult to use the tracking error to quantify active management across all funds because it will be heavily affected by the funds' investment strategy. If a fund has a stock picking strategy, it could receive a very low tracking error because the fund manager can eliminate the volatility through diversification. In other words, a stock picking fund[2] could obtain status as a passive fund, even though it is in reality highly active. At the same time, a sector rotating fund[3] could obtain a higher tracking error, and thus be deemed more active, because the fund is not able to diversify to the same extent as a stock picking fund (Cremers & Petajisto, 2009, p. 1). Hence, the tracking error could be flawed and one should be careful when interpreting it.

2.1.2 Active Share

As a solution to the issues with the tracking error, Cremers & Petajisto proposes an alternative activity measure, namely the active share. The formula for active share is given as:

$$Active\ Share = \frac{1}{2}\sum_{i=1}^{N} |w_{fund_i} - w_{index_i}|$$

Where

w_{fund_i} is the weight of stock$_i$ in the given fund

w_{index_i} is the weight of stock$_i$ in the relevant benchmark index.

As the formula indicates, the active share measures the absolute deviation from the fund portfolio holdings compared to the relevant benchmark index portfolio holdings. In other words, it measures the proportion of the fund that does not overlap with the benchmark index (Norstein & Varran, 2015, p. 21). The interpretation of the measure is the more the fund's portfolio deviates from the benchmark's portfolio, the higher the active share and the more active the fund is. Moreover, mutual funds never take short positions, which imply that the active share of a fund will always lie between 0 and 100% (Cremers & Petajisto, 2009, p. 2). Due to the nature of the formula, a fund that mimics the benchmark index will have an active share of 0%, while a fund that does not overlap with the benchmark at all will have an active share of 100%. Moreover, Cremers &Petajisto uses an active share of 60% as the threshold for a fund to be classified as active.

Furthermore, the absolute difference between the portfolio weights in the fund and the portfolio weights in the benchmark is divided in half. The reason for this is the fact that if a fund has an overweight in one stock and an underweight in another stock, the absolute difference will add both, which means that it will

[2] A fund that actively seeks out individual mispriced stocks in order to achieve abnormal returns.
[3] A fund that actively invests in entire sectors or industries that performs better than the market as a whole.

be counted twice. Table 2.1 below illustrates this point with a hypothetical example from Norstein & Varran (2015):

Table 2.1: active share of a fund and a benchmark consisting of 4 stocks. Source: Norstein & Varran, 2015

Asset	Weight in Fund	Weight in Benchmark	Absolute Diffference
Stock 1	30 %	20 %	10 %
Stock 2	5 %	50 %	45 %
Stock 3	40 %	15 %	25 %
Stock 4	25 %	15 %	10 %
Sum	100 %	100 %	90 %
Active Share			45 %

Table 2.1 above illustrates the active share formula in practice. The first column lists the stocks available, while the second column lists the fund's weight in the available stocks. The third column lists the benchmark's weight in the available stocks. Finally, the fourth column lists the absolute difference between the holdings in the fund and the holdings in the benchmark. The active share is listed at the bottom of the fourth column, and is given as the sum of the absolute difference divided by two.

As mentioned in the introduction, due to the fact that the active share measure is relatively new, there have been a very limited number of studies where the active share measure has been applied to the Norwegian market. The most significant study was performed by Norstein & Varran in 2015, who documented that the active share varies vastly across self-proclaimed actively managed funds.

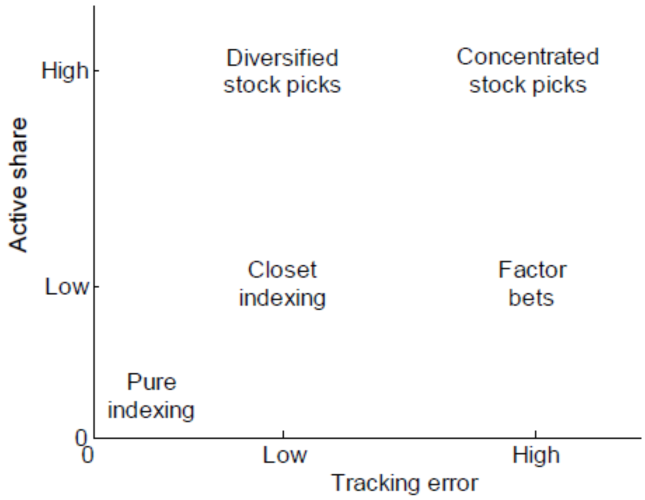
2.1.3 Detecting Investment Strategies

Cremers and Petajisto proposes a way one could detect a given fund's investment strategy; by combining the tracking error and the active share. They advocate that there are two distinct ways a fund manager can actively outperform a benchmark index, namely engaging in stock picking (see section 2.4.1) and market timing (see section 2.4.2). By capturing the fund managers' attempt to engage in these activities, one is able to capture both dimensions of a manager's abilities, which in turn will reveal his strategy. Hence, they proceed with using active share as a proxy for stock picking and tracking error as a proxy for market timing (Cremers & Petajisto, 2009, p. 7-8).

The tracking error includes the covariance matrix of returns, which implies that it puts more weight on systematic active bets, and makes it a suitable proxy for market timing. Active market timers are usually not able to diversify their portfolio sufficiently to minimize the systematic risk, and will therefore bear systematic risk relative to the benchmark (Norstein & Varran, 2015, p. 22). Therefore, funds that engage in market timing will tend to have a high tracking error. Conversely, as discussed in section 2.1.1, fund managers that engage in stock picking are usually able to diversify their portfolio to such extent that they only bear unsystematic risk. That is, stock pickers tend to have a lower tracking error compared to market timers.

Because active share puts equal weight on all active bets, independent of risk diversification, it is a suitable proxy for stock picking (Cremers & Petajisto, 2009, p. 8). As discussed in section 2.1.2, active share measures to what extent the funds' portfolios are deviating from the benchmark index portfolio. A manager that actively seeks out mispriced stocks, will automatically deviate from the benchmark, and thus receive a higher active share. Combining the tracking error and the active share leads to the two-dimensional classification of funds illustrated in Figure 2.1 below:

Figure 2.1: Investment strategies w/ active share and tracking error. Source: Cremers & Petajisto, 2009, p. 44.



Keeping in mind that active share is a proxy for stock picking, and tracking error is a proxy for market timing, one can identify four different investment strategies by combining the two. As mentioned above, stock pickers have a low tracking error and a high active share, and will be located in the upper-left corner of Figure 2.1, classified as "*diversified stock pickers*". Located within this classification, a fund will have an overall sector weighting approximately equal to the benchmark, but several investments in individual stock positions that differs widely from the benchmark (Norstein & Varran, 2015, p. 22).

A fund that engages in market timing, as opposed to stock picking, will fall into the category "*factor bets*". Here, the fund manager is more concerned about assembling a broad portfolio in sectors that he believes will outperform the market as a whole. Therefore, the fund manager will not be able to eliminate all systematic risk through diversification, and will receive a high tracking error and a low active share.

A fund that engages in both market timing and stock picking is classified as a *"concentrated stock pickers"*. These are known as the most active funds, and are the ones that truly have the right to charge their investors for active fund management. By building a portfolio that focuses on a few sectors that are expected to outperform, and heavily seek out individual stocks that are mispriced, a concentrated stock picking fund will have both a high tracking error and a high active share (Norstein & Varran, 2015, p. 22).

In contrast, a fund that neither engages in stock picking or market timing will by default have a portfolio that is equal to that of the benchmark index. According to Cremers & Petajisto, these funds are classified as *closet indexing funds*. With regards to the critique from the media and the government in Norway, which is portrayed in section 1.1, these are the funds that mislead their investors. A closet indexing fund is charging its investors on the basis of delivering active fund management, but because its portfolio is equal to that of the benchmark index, it is actually delivering passive fund performance.

2.2 Theoretical Framework: The Efficient Market Hypothesis

The theoretical foundation behind this thesis is the efficient market hypothesis (EMH), which concerns the price movements of securities in regards to information availability. Ironically, the EMH are built upon some assumptions that effectively discard active fund management as a potential way of achieving abnormal returns[4], which will be evident by the end of this section.

Eugene Fama proposed the EMH with his revolutionary and highly praised paper "Efficient Capital Markets: A Rewiew of Theory and Empirical Work", which he published in 1970 through *The Journal of Finance*. Here, he distinguishes between three different forms of market efficiency; weak, semi-strong and strong, which differs from each other in terms of how much information the prevailing security prices reflect (Fama, 1970, *The Journal of Finance,* p. 388). In addition, he describes the security price movements as *random walks*. That is, today's price movements are completely independent from yesterday's price movements. As we know, security price react to new information, and new information is by definition unpredictable. Hence, security prices are impossible to predict before the new information is present, and thus follow a random walk. Several academics claim that random price movements are the best indicator of an efficient financial market (Bodie et al., 2014, p. 350).

As mentioned, Fama distinguished between three forms of market efficiency. The *weak form* implies that security prices reflect all historical information. By default, and the fact that security prices follow a random walk, this means that trend analysis in order to detect mispriced securities will not be effective. The *semi-strong form* implies that also publicly available information is incorporated in security prices, in addition to the historical information. From a trading perspective, this implies that technical or fundamental analysis

[4] Return in excess of the expected rate of return.

would be a waste, as one would expect the information to be immediately reflected in security prices. Finally, the *strong form* states that security prices reflect historical, publicly available, and insider information. In other words, the security prices reflect all information relevant to a firm and a trader will never be able to beat the market (Bodie et al., 2014 p. 353 - 354).

As you would note, the EMH implies that the foundation actively managed funds build their industry on is none-existent. As described in greater detail in section 4.1, actively managed funds gather information and analyze it in order to detect mispriced securities. Information gathering is resource intensive, and funds need to continuously outperform the market in order to both cover their costs and deliver abnormal returns to their investors. However, if the EMH is correct, it would not be possible to detect mispriced securities as the prices would always reflect available information and the market would be efficient at all times. Here a question emerges; if the markets were truly efficient, would anyone invest in active funds? The rational answer is no. If the markets were truly efficient all investors would be better off by investing passively as it would be impossible to outperform the market.

Even though the EMH has been reaffirmed several times, it seems like the EMH is imprecise in reality, as all trading activities would be none existent if the hypothesis was true. Hence, it has been prone to criticism from several academics. Amongst other things, it has been criticized for not taking human behavior into account, which could lead to market imperfections (*Behavioral Finance School*). Moreover, the assumption that information is available to all market participants free of charge has been challenged (Grossman & Stiglitz, 1980, p. 393). In 1991, Fama introduced a modified version of the EMH as a response to the critique. Here, he allowed for temporary mispricing of securities. However, he claimed that temporary mispricing would be erased in the long run.

In other words, studies prove that market inefficiencies exist, at least in short periods of time. Hence, actively managed funds could take advantage of these market inefficiencies by continuously pick the correct mispriced stocks. Market inefficiencies are expected to occur in less analyzed and monitored markets (Bodie et al., 2014, p. 352). Norway is a significantly smaller market, and much less analyzed, than the U.S. market, where the majority of studies have been performed. Therefore, it would not be farfetched to think that it could be easier to identify mispriced stocks in Norway than in the U.S.

2.3 The Capital Asset Pricing Model

The Capital Asset Pricing Model, or simply CAPM, is one of the absolute cornerstones within modern financial theory, and serves as a foundation for a substantial number of financial models concerning portfolio theory. The CAPM was developed on the basis of individual articles published by Sharpe (1964), Lintner (1965), and Mossin (1966) (Bodie, Kane, Marcus, 2014, p. 291). When it first saw the light of day, the CAPM was groundbreaking in many ways. First and foremost, it was the first financial model making it possible to identify and measure a relationship between risk and return. That is, by applying the CAPM, one could now predict if the forecasted expected return for a given security is more or less than what one would characterize as "fair" given its risk (Bodie et al., 2014).

The CAPM formula is given as:

$$E[r_i] = r_f + \beta_i(E[r_m] - r_f)$$

Where,

$E[r_i]$ is the expected return of security *i.*

r_f is the prominent risk-free rate of return in the market.

β_i is the sensitivity of the expected return of security *i* to the expected market return.

$E[r_m] - r_f$ is the market risk premium, given as the difference between the expected market return and the risk-free rate of return.

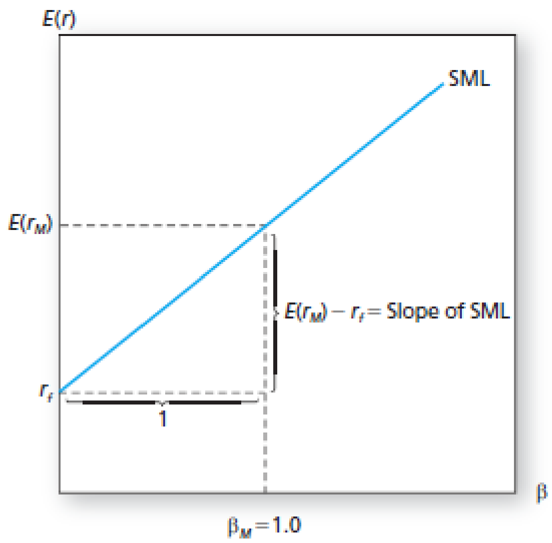
As mentioned in the paragraph above, risk is a central aspect of the CAPM. The risk is divided into two components; the first component is captured by the beta (β), which is also known as non-diversifiable risk, or systematic risk. That is, risk that is prominent in the market and cannot be eliminated through diversification. The second risk component is the diversifiable risk, or unsystematic risk, which is an asset specific risk that investors can eliminate through sufficient portfolio diversification. Looking at the formula above, we see that only the non-diversifiable risk is included, and the CAPM thus claims that investors are only compensated for taking on non-diversifiable risk as the diversifiable risk can easily be removed through diversification.

The CAPM is often portrayed graphically through the Security Market Line (SML), which illustrates the relationship between expected return and risk. Figure 2.2 below illustrates the already mentioned relationship. When the assumptions behind the CAPM hold, all "fairly priced" assets will plot along the SML. Bodie et al. claims when the assets do so, "their expected returns are commensurate with their risk" (2014, p. 298). Hence, the SML provides an easily interpretable picture of the return one should expect given the risk of a specific asset or portfolio. Moreover, the SML makes it easy to identify overvalued or undervalued asset; if the asset is located below the SML, the expected return is too low compared to the undiversifiable risk and the asset is overpriced.[5] In other words, the SML provides a benchmark for performance evaluation

[5] It will be a negative alpha asset, which per definition is an overvalued asset.

(Bodie et al., 2014, p. 298). If we take the EMH into account when looking at the CAPM, all securities/portfolios located above/below the SML should return to a location along the SML in the long run.

Figure 2.2: CAPM and the SML. Source: Bodie et al., 2014, p. 298



Even though the CAPM holds a special place in modern portfolio theory and performance measuring, it is prone to criticism. Fama & French criticise the CAPM for being too simplistic, and that it might suffer from theoretical impreciseness (Fama & French, 2004, p. 25) Despite this, it is the most applied and widely taught asset pricing model in today's academic world. The CAPM is of special importance to this thesis, because the single-index models (discussed in section 2.4), are derived directly from it. In fact, both the Jensen's alpha and Treynor & Mazuy's market timing model, which I will apply later in the study, are developed from the CAPM framework.

2.4 Single-Index Models

In order to measure and analyze the funds' performance, single-index models are applied in this study. Single-index models are derived directly from the CAPM, and provide a quantifiable measure of outperformance/underperformance that is easily interpretable. Another favorable trait is the fact that single-index models can be extended in order to test for different skillsets among fund managers. In this study, both micro forecasting abilities and macro forecasting abilities are being tested for. The name *single-index models* stem from the fact that they use a common market index in order to compare relative portfolio performance (Bodie et al., 2014, p. 259).

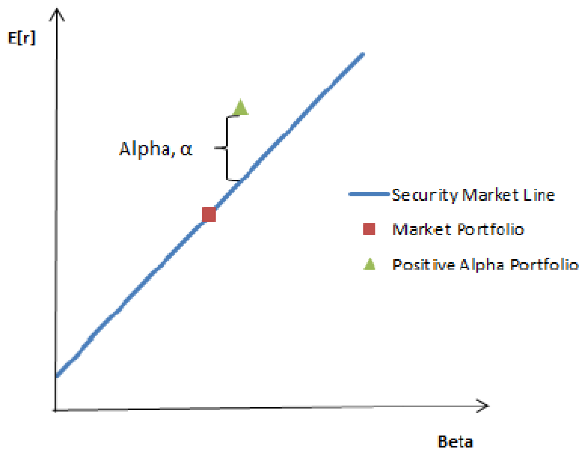
2.4.1 Micro-forecasting abilities: Jensen's Alpha

Jensen's alpha was developed in the 1960's, and is one of the most applied portfolio performance measures in today's financial world. The measure is directly derived from the CAPM formula, and according to Jensen, the measure tests "the investment managers' *predictive ability* – that is his ability to earn return through successful prediction of security prices which are higher than those which we could expect given the level of riskiness of his portfolio" (Jensen, 1968, p. 389). In other words, Jensen's alpha provides a direct measure of a portfolio's outperformance/underperformance compared to the market. Hence, this is a measure of special importance in studies measuring fund performance, where the benchmark is a market index. The regression equation is given as:

$$r_{i(t)} - r_{f(t)} = \alpha_i + \beta_i(r_{M(t)} - r_{f(t)}) + \varepsilon_{i(t)}$$

The measure under scrutiny is the intercept in the regression equation above. The intercept, denoted by alpha, provides a quantifiable measure of the direct outperformance/underperformance of a given portfolio, relative to the market. In case of active fund management, the alpha value will yield a measure of the outperformance/underperformance relative to a passive fund, which mimics the benchmark index. When interpreting the alpha value, a positive alpha value, i.e. $\alpha_i > 0$, indicates that the fund manager has outperformed the market/passive benchmark. Similarly, a negative alpha value, i.e. $\alpha_i < 0$, indicates that the fund manager has underperformed relative to the market/passive benchmark (Bodie et al., 2014, p. 267). Because Jensen's alpha is directly derived from the CAPM, its relationship with the SML can be illustrated as follows:

Figure 2.3 Jensen's Alpha and the SML. Source: Own creation based on Jensen (1968).



In addition to measuring outperformance, Jensen's alpha can be used to identify micro forecasting abilities. That is, it can illustrate whether fund managers are able to successfully and continuously pick individual underpriced securities in order to deliver abnormal returns to their investors. A statistically significant positive Jensen's alpha estimate indicates micro forecasting abilities, also known as stock picking skills. Similarly, a statistically significant negative Jensen's alpha estimate indicates poor micro forecasting abilities. That is, an unfavorable situation where the fund manager continuously picks overpriced stocks, which ultimately leads to significant underperformance relative to the market. It is important to note that a positive insignificant alpha estimate still indicates outperformance. However, in such a situation there is no evidence of micro forecasting abilities.

The research on equity mutual fund in the Norwegian market has so far not revealed any evidence of micro forecasting abilities among Norwegian fund managers. Amongst others, Gjerde & Sættem (1991), Skålebråten (2013), and Norstein & Varran (2015) were unable to isolate micro forecasting abilities when applying the Jensen regression to Norwegian equity mutual funds with a domestic mandate.

2.4.2 Macro forecasting abilities: Treynor & Mazuy's Market Timing Model

In addition to testing for micro-forecasting abilities, finding evidence of fund managers' macro forecasting abilities have been an intriguing research topic for academics. After Jensen made it possible to measure the micro forecasting abilities through his Jensen regression in 1968, researchers started looking for measures to quantify other managerial skills. The EMH had established itself as a fundamental theory in the financial world, and academics were looking to investigate if investment managers actually were able to beat the market. Fama (1972) and Jenson (1972a) were the first to develop a structure were one could quantify the investment managers' forecasting abilities in more ways than one; they developed a theoretically structure in which one could quantify the macro forecasting abilities as well as the micro forecasting abilities (Henriksson, 1980, p. 3-4).

As the name suggests macro forecasting abilities concerns investment managers' ability to predict larger market movements; Are they able to predict bull[6] and bear[7] markets? Being able to predict larger market movements is imperative to being able to deliver abnormal performance, and is thus an ability highly sought after by investors. Market timing is closely related to risk management, and the rule of thumb is to have a higher risk-level compared to the market during bull markets and a lower risk-level during bear markets. There are two ways a portfolio manager can adjust the risk level of the fund; adjust the relative proportions of debt and equity, and adjust the risk-level of its equity holdings (Treynor & Mazuy, 1966, p. 134). Due to the delimitations of this study, only the latter will be considered. In practice, this is done by altering the portfolio according to the betas of the individual stocks. When an investment manager believes the market will rise, he alters his portfolio towards high-beta stocks in order to capture more of the

[6] A financial market where the prices are rising or expected to rise.
[7] A financial market where the prices are falling or expected to fall.

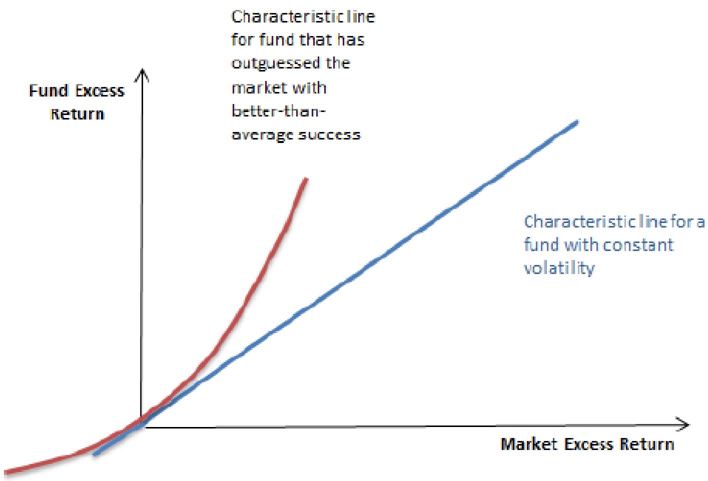
upswing in the market. Similarly, if he believes the market will fall, he alters his portfolio towards low-beta stocks, as these tend to fall less than the overall market (Treynor & Mazuy, 1966, p. 132). If the manager is successfully able to do so over time, he will eventually deliver abnormal returns.

There are several financial models able to capture macro forecasting abilities. However, in this study, *Treynor and Mazuy's Market Timing Model* (1966) will be applied, as it is an extension of the already mentioned Jensen regression. The Treynor & Mazuy regression equation is given as:

$$r_{i(t)} - r_{f(t)} = \alpha_i + \beta_i\left(r_{M(t)} - r_{f(t)}\right) + \gamma\left(r_{M(t)} - r_{f(t)}\right)^2 + \varepsilon_{i(t)}$$

If we compare the regression equation above with the Jensen regression, we see that Treynor & Mazuy has added the squared excess market return as an additional independent variable. That is, when measuring macro forecasting abilities, the actual market timing skills is measured by the gamma (γ) coefficient. The reader should also note that the alpha is still included in the regression, and has the same definition as in the Jensen regression.

Figure 2.4: Fund Characteristic Line for Market Timing Funds. Source: Skålebråten (2013)



In Figure 2.4 above, a graphical illustration of a successful market timing fund's performance is presented. Here, the fund's characteristic line is presented compared to a characteristic line for a fund with constant risk level. In a characteristic line, the rate of return for a fund is plotted against the rate of return for a market index. If the rate of return for the fund is equal to that of the market index, the slope of the line is straight (blue line). That is, the fund manager does not alter his portfolio according to the individual stock's beta values, and the risk level is equal to that of the market (Treynor & Mazuy, 1966, p. 133). However, if the fund manager successfully engages in risk-adjusting his portfolio according to macro movements, the fund characteristic line will be concave (red line). That is, the fund's excess return increases to a much larger extent than the linear excess return of the market. The gamma coefficient, which was introduced above, is the quantifiable measure of the slope of the characteristic line. Hence, a higher gamma value indicates better macro forecasting abilities and leads to a higher excess return. Similar to the Jensen regression, a statistically significant gamma indicates evident skills, while an insignificant positive gamma does not show evidence of skill and the macro forecasting could just as well be due to luck. For a negative gamma, the opposite is true.

In contrast to the findings on micro forecasting skills, evidence has been found for macro forecasting abilities among Norwegian fund managers. Both Skålebråten (2013) and Norstein & Varran (2015) do in fact find evidence of market timing abilities. However, in both studies the alpha values are severely punished by the significant positive gamma estimates. That is, any potential gain in macro forecasting abilities seems to be erased by similarly poor micro forecasting abilities. In other words, there is no evidence of both abilities being present at the same time in the Norwegian market.

2.5 Varying risk levels: applying single-index models in a conditional setting

As mentioned in section 2.3, the CAPM is taking risk into consideration through the beta estimate. Furthermore, as the single-index models (see section 2.4.1 and 2.4.2) are derived directly from the CAPM, they capture the risk by the same estimate. These measures are estimated by regressing the excess return for a specific fund on the excess return for the market. That is, the risk-free rate is deducted from the dependent variable and the independent variables in the regression equation. Single-index models are traditional performance models, also known as *unconditional models*, and use the historical average of the risk-free rate in order to determine the excess returns. That is, you use a single risk-free rate, which implies that the risk captured in the regression does not vary through time. Or to put it differently, unconditional performance models considers a stationary risk level.

As the statistical accuracy of the models increase with the number of observations included, the models require a certain time period of returns and risk-free rates. Fama (1972) advocate that a minimum of five years of monthly returns and monthly risk-free rates are necessary in order to obtain reliable regression estimates. However, historical average risk-free rate over a long time horizon may not portray a realistic picture of the risk levels. Dependent on the current macro-economic environment, along with recent changes in the macro-economic outlook, the historical average risk-free rate might be unrealistically high or unrealistically low. With regards to the unconditional models, this means that the stationary risk level considered might not be as accurate as one would prefer. In practice, it implies that it would be difficult to isolate if the alpha measure actually captures average performance or if it simply is affected by time variation in risk and risk premiums (Ferson & Schadt, 1996, p. 425).

In their paper, Ferson & Schadt (1996) proposes a solution to the problem. They claim that "the returns and risks of stocks and bonds are predictable over time, using dividend yields, interest rates, and other variables" (Ferson & Schadt, 1996, p. 426). Based on this claim, they propose *conditional performance models*, which are modified versions of Jensen's alpha and Treynor & Mazuy, which are discussed in section 2.4 of this study. These conditional models estimate a time-varying beta, based on a set of publicly available information variables. In their study, Ferson & Schadt include the following information variables (Skålebråten, 2013, p. 27):

1) The lagged level of the one-month Treasury bill yield.
2) The lagged dividend yield of the CRSP value-weighted NYSE and AMEX stock index.
3) A lagged measure of the slope of the term structure.
4) A lagged quality spread in the corporate bond market.
5) A dummy variable for the month of January.

The abovementioned information variables are factored in to a vector, Z_{t-1}, and added to the standard Jensen regression:

$$r_{i(t)} - r_{f(t)} = \alpha_i + \beta_i\left(r_{M(t)} - r_{f(t)}\right) + \beta_i' Z_{t-1}\left(r_{M(t)} - r_{f(t)}\right) + \varepsilon_{i(t)}$$

Similarly, adding the same vector of information variables to the standard Treynor & Mazuy market timing model, the conditional Treynor & Mazuy model becomes:

$$r_{i(t)} - r_{f(t)} = \alpha_i + \beta_i\left(r_{M(t)} - r_{f(t)}\right) + \beta_i' Z_{t-1}\left(r_{M(t)} - r_{f(t)}\right) + \gamma\left(r_{M(t)} - r_{f(t)}\right)^2 + \varepsilon_{i(t)}$$

Ferson & Schadt claim that the conditional models are especially attractive when estimating fund performance for two reasons. First, the traditional, unconditional models struggle to cope with the dynamic behavior of returns. Second, fund managers' trading behavior result in more complex dynamics than those of the underlying assets they trade (Ferson & Schadt, 1996, p. 426). However, after running their regressions, only the first three of the five original information variables were deemed statistically significant (Skålebråten, 2013, p. 27).

While Ferson & Schadt's original study was performed on the vast U.S. market, some attempts have been done to apply the same approach to the Norwegian market. Skålebråten (2013) were able to improve 68 % of his unconditional models by applying the Norwegian equivalents of the three statistically significant information variables from Ferson & Schadt's study.

3.0 Methodology

This section provides an insight to the data collection and selection process. Moreover, it describes the methodology applied in this study. Finally, a range of robustness tests are presented and applied in order to statistically validate the accuracy of the performance measures. Certain of the sub-sections in this part of the study should be read in parallel to section 4.0, which describes the characteristics and operations of Norwegian actively managed equity mutual funds. Moreover, section 4.0 elucidates the most important implications of the regulations of funds

3.1 Data Sample

3.1.1 Selection Process and Criterias

As mentioned in the introduction, this study focuses on the Norwegian market. Hence, there is a natural delimitation to the number of funds that can be included in the analysis. In order to obtain results that are comparable across the data sample, I have decided to only analyze a particular type of funds, namely equity mutual funds. Equity mutual funds are the most popular mutual funds in Norway, and thus of most practical interest to investigate. A more in-depth discussion of Norwegian equity mutual funds is presented in section 4.0 of this study.

In addition to being the most popular funds in Norway, another critical point in regards to data selection arises; as this study includes single-index models and the active share measure, a common benchmark index is required in order to measure performance and differences in portfolio holdings. Other popular fund types, such as hybrid funds, which invest in both equities and bonds, cannot be compared to the same benchmark as pure equity mutual funds because their portfolio consists of a different range of investment products. Moreover, an important aspect is that if the study included analyses of a wide range of fund types, accurately isolating effects and causalities would be problematic. Hence, in order to obtain the desired level of accuracy in my results, along with the natural restrictions of the models applied, only one specific type of funds is being analyzed in this study. The task of identifying a suitable benchmark is presented in section 3.2.

Only equity mutual funds that are domiciled in Norway, and primarily investing in domestic equities listed on Oslo Stock Exchange (OSE), are being analyzed. According to the Norwegian Fund and Asset Management Association, there are approximately 1400 funds listed on OSE of December 31st 2015. Of these, 407 are equity mutual funds, where 78 are investing in domestic stocks[8]. The major reason for choosing domestically mandated equity mutual funds is also linked with the task of identifying a suitable

[8] http://vff.no/historisk-statistikk - downloaded 10.08.2016

benchmark. Equity mutual funds investing in international equities differ in terms of target markets. Some focus on emerging markets, while other may focus on a specific market, such as the Scandinavian, U.S., or Japanese market. Hence, a suitable benchmark for one international fund might not be suitable for the next international fund. By focusing solely on the Norwegian market, I impose an investment restriction by default that the fund managers can only invest in equities listed on OSE. In practice, this implies that the selected benchmark would automatically be suitable for all funds in my sample.

The next criterion that needs to be fulfilled is that the funds under scrutiny in this study need to be self-proclaimed actively managed. Naturally, in order to test whether actively managed funds are delivering the product their investors pay them for, any passively managed funds needs to be excluded from the final data sample. Thus, by looking at the individual funds' prospectuses, along with the information about the funds on Morningstar's fund database[9], I was able to single out the actively managed equity mutual funds from the passively managed. This reduced the number of available funds from 78 to 51.

Another criterion that needs to be fulfilled is in regards to the lifespan of the funds. As mentioned in section 2.5, a minimum lifespan must be set at a level that ensures a sufficient number of observations for the performance measures. Fama (1972) advocated that a minimum of 5 years of monthly observations should be sufficient to ensure statistically valid results. However, Fama's study was performed on the U.S. market, which has a significantly higher number of funds than the Norwegian market, and is a more mature financial market. The issue with shorter lifespans is the occurrence of statistical noise and less reliable results. However, a minimum lifespan of 5 years would exclude 19 of the 51 funds, which implies that I would be left with a very small data sample. Hence, in order not to lose valuable data, I chose a minimum lifespan of 3 years for the data sample in this study. This criterion reduces the data sample from 51 to 43 funds.

The major focus point of this study is identifying the true activity levels of actively managed funds. As presented in section 2.1, the active share measure is the preferred activity measure in this study. As the measure addresses portfolio holdings, it creates the final selection criteria for my sample; for a fund to be included in this study, a complete portfolio has to be publicly available. Some funds chose not to disclose their entire portfolio, as they are not required to do so. Hence, the final number of funds in my sample is decided by the number of actively managed Norwegian equity mutual funds that fully disclose their portfolio holdings. Thus, the final selection criteria reduce the data sample from 51 to 38 funds. Portfolio

[9] http://www.morningstar.no/no/ - downloaded 15.08.2016

holdings are downloaded as of December 31st 2015, from the individual funds' prospectuses, as well as the *Bloomberg* database. A summary of the selection process is presented in table 3.1 below:

Table 3.1: Summary of selection process. Source: Own creation, numbers from *Datastream & NFAMA*

Selection Criterion	Number of Funds
Listed on OSE	1400
Equity Mutual Funds	407
Domestic Investment Mandate	78
Actively Managed	51
Minimum Lifespan Of 3 Years	43
Full Portfolio Disclosure	38
Final Data Sample	**38**

3.1.2 Timeframe

An important aspect of the data sample is the chosen timeframe for the performance models. There have been numerous studies on active fund management and the approaches and timeframes varies widely. For instance, Michael C. Jensen's first paper on mutual fund performance, which is widely regarded as a revolutionary study on the field, measured performance from 1945 – 1964, which implies a timeframe of 19 years (Jensen, 1967, p. 389). Gjerde & Sættem's performance study, which was the first major study on the Norwegian mutual fund market, measured the performance from 1982 – 1990, which implies a timeframe of 8 years (Gjerde & Sættem, 1991, p. 297). Hence, it appears that the overall timeframes tend to be arbitrary. For this study, I have chosen a timeframe of 10 years. That is, I will investigate the performance of Norwegian equity mutual funds from January 1st 2006 until December 31st 2015. The reasoning behind the 10-year timeframe is to capture a full market-cycle. In 2008, the financial crisis blindsided the financial markets[10], and in late 2014, a dramatic fall in oil prices heavily affected Norway's "oil-geared" financial market[11]. Hence, this study captures two periods of severe financial turmoil, which were the financial crisis in 2008 and the meltdown of the oil-price in 2014. Furthermore, the study captures two recovery periods after the two mentioned crises, along with two periods of normal state in the financial market, which were before the financial crisis in 2007 and between the recovery after the financial crisis and oil-price meltdown in 2014. Hence, this study includes a data sample consisting of 38 funds, with 10 years of monthly data. For the funds with a shorter lifespan than 10 years, the timeframe will be equal to their entire lifespan.

[10] https://www.stlouisfed.org/financial-crisis/full-timeline - downloaded 16.08.2016
[11] https://bors.e24.no/#!/instrument/OSEBX.OSE - downloaded 16.08.2016

A fund with 10 years of monthly returns is equivalent to 120 observations, which is the upper limit of observations in this study. On the other hand, the criteria of a minimum lifespan of 3 years imply a lower limit of observations of 36. In practice, this implies that the issue of statistical noise might occur for the funds with the shortest lifespan. The choice of monthly data is debatable, and some previous studies have applied shorter data series. For instance, Norstein & Varran applied weekly data in their study (Norstein & Varran, 2015, p. 41). However, the advantage of using monthly data over weekly data is that monthly returns are closer to being normally distributed because of the increased time intervals between each observation. Approximately normally distributed data is preferable when applying single-index models, because the assumption of normality is strong for these models. Hence, I will proceed with monthly data for this study, which is in line with Jensen's original study from 1968 and Gjerde & Sættem's revolutionary paper on the Norwegian market from 1991. The monthly data is downloaded from *Thomson Reuters Datastream*, and is given as the closing Net Asset Value (NAV) at the end of each month. For a full definition of NAV, please see section 4.1.

3.2 Choosing the optimal benchmark index

The importance of identifying a suitable benchmark became evident in section 3.1. As previously mentioned, the benchmark is imperative for both the active share measure and the single-index performance models. However, identifying the single-most suitable benchmark can sometimes be challenging, as there tend to be several promising alternatives. Luckily, because this study only addresses Norwegian equity mutual funds investing primarily in stocks listed on the OSE, the list of potential candidates is significantly reduced. Thus, due to the domestic investment mandate, the suitable benchmark is limited to one of the OSE indices. This section should be read in parallel with section 4.0, which addresses the characteristics and regulations of Norwegian equity mutual funds.

There are 46 different indices on the Oslo Stock Exchange[12]. However, 35 of these are sector indices. Because mutual funds invest across sectors, having a single sector index would be highly misguiding, and would not capture every aspect of the mutual funds' performance and portfolio holdings. Furthermore, five of the indices are listed government bonds with varying time to maturity. Since equity mutual funds do not invest in bonds, they are irrelevant by default. Of the remaining six indices, one is a small cap index[13] (OSESX) and another is a mid-cap index[14] (OSEMX). Cap limited indices are based on the market capitalization of the stocks. However, as equity mutual funds tend to diversify their portfolio across

[12] https://finance.yahoo.com/lookup/indices?bypass=true&s=OSE&t=I&m=ALL&r=&b=20 – downloaded 17.08.16
[13] http://www.oslobors.no/markedsaktivitet/#/details/OSESX.OSE/overview - downloaded 17.08.16
[14] http://www.oslobors.no/markedsaktivitet/#/details/OSEMX.OSE/overview - downloaded 17.08.16

companies of all different sizes, neither of these are optimal benchmarks. Hence, there are four promising candidates left for an optimal benchmark index.

Table 3.2: Exclusion criteria for benchmark indices. Source: Own creation

Exclusion Citerion	Number of Indices
Total Indices on OSE	46
- Sector Indices	35
- Listed Government Bonds	5
- Cap Limited Indices	2
= Potential Benchmark Candidates	4

The first candidate is the OSEAX, which is the "All Share Index" of Oslo Stock Exchange. That is, it consists of all listed stocks on the OSE[15]. Immediately, it might seem like a perfect candidate for a benchmark index, as it ticks many of the required boxes. For instance, it addresses the issue with the cap limited indices of not capturing the funds' entire portfolio diversifications. Despite this, the fact that the OSEAX consists of all listed shares might be its curse. There are a vast number of highly illiquid stocks listed on the OSE, which by default is included in the OSEAX. In practice, this means that the OSEAX cannot be replicated by a mutual fund without the fund incurring substantial transaction costs (Skålebråten, 2013, p. 33). Hence, despite its initial promising characteristics, the OSEAX is not a suitable benchmark index for this study.

The second candidate is the OSE's benchmark index, named OSEBX. The OSEBX is an investible index, which consists of a representative selection of the listed stocks on the OSE[16]. The fact that it is an investible index is favorable in the sense that it eliminates the problem with illiquidity. Per 31.12.2015, the OSEBX consisted of 58 stocks[17]. However, Norway is a small financial market where the market capitalization of the stocks listed on OSEBX varies vastly. In fact, the four largest companies on OSEBX constitutes approximately 60% of the index' market capitalization (Norstein & Varran, 2015, p. 40). Hence, for an equity mutual fund that cannot invest more than 10% of its capital in a single security due to the UCITS regulations (see section 4.1), it would be impossible to outperform the market if one of the top-4 companies were delivering abnormal returns. Thus, because the OSEBX is severely top-heavy, it is not a suitable benchmark index for this study.

The third candidate for a benchmark is the OSE's total return index, also known as OBX. The OBX consists of the 25 most frequently traded stocks on OSE, ranked by their total return during the last six months[18]. Thus,

[15] http://www.oslobors.no/markedsaktivitet/#/details/OSEAX.OSE/overview - downloaded 17.08.16
[16] http://www.oslobors.no/markedsaktivitet/#/details/OSEBX.OSE/overview - downloaded 17.08.16
[17] http://www.oslobors.no/Oslo-Boers/Om-Oslo-Boers/Nyheter-fra-Oslo-Boers/Endret-utvalg-i-Hovedindeksen - downloaded 17.08.16
[18] http://www.oslobors.no/Oslo-Boers/Om-Oslo-Boers/Nyheter-fra-Oslo-Boers/Nytt-OBX-utvalg-fra-20.-juni - downloaded 17.08.16

the index portfolio is revised every six months, but still suffers from the same problem as the OSEBX: severe top-heaviness. The top-4 companies mentioned above is listed on OBX as well, and because the OBX counts for short of half of the stocks listed on OSEBX, the problem actually increases. Hence, the OBX is not suitable for this study.

That is, I am left with only one potential candidate, and as I will explain, it is a highly suitable benchmark for this study. The index in question is the Oslo Stock Exchange's Mutual Fund index, abbreviated to OSEFX. As the name indicates, the OSEFX is a fund-oriented index. In fact, it is weight-adjusted version of the OSEBX. The weight-adjustment is in accordance with the UCITS regulations (see section 4.1), and thus, none of the stocks constitutes more than 10% of the index' market capitalization. Moreover, stocks that constitutes more than 5% of the index' market capitalization, cannot combined constitute more than 40% of the total market capitalization. In practice, this implies that all the issues with top-heaviness is effectively eliminated. Furthermore, the absolute majority of the funds in the final data sample list the OSEFX as their comparable benchmark index, which further supports my claim of this being the ideal benchmark.

As a final test, I have applied Skålebråten's suitability test, where I have calculated the adjusted R^2 for the unconditional Jensen regression for each of the four potential candidates. Table 3.3 below presents the results, and proves that the OSEFX obtains the highest adjusted R^2, and thus fits my single-index models the best. Hence, I will proceed with the OSEFX as the benchmark index in this study.

Table 3.3: Ranking of benchmark candidates based on adjusted R^2. Source: Skålebråten, 2013, p. 34

Benchmark Candidate	Adjusted R^2	Ranking
OSEFX	0.9110	1
OSEBX	0.8925	2
OBX	0.8803	3
OSEAX	0.8697	4

3.3 Activity Levels

As mentioned in the introduction, Norway is the first country to take legal actions against closet-indexing funds. That is, the true activity levels of actively managed funds are under scrutiny from both government and media. According to theory, an actively managed fund can charge their investors higher fees because information gathering is resource intensive. Moreover, active funds take on higher risk than passive funds, because their portfolios differ from the market portfolio, and they should be compensated for doing so. In other words, the fees the funds are charging their investors and the level of activity within the funds are closely related. However, according to the Norwegian media, the classic relationship between activity and fees is impeded by the funds. It appears that the funds' greed for money comes at the expense of their investors. The practical implication of this is that the investors pay for active management, but receive passive management instead. The funds' fees are discussed in greater detail in section 3.4.

From section 2.1, we know that activity levels can be measured in two dimensions; active share and tracking error volatility. In the sub-section below, I present the methodology behind the two measures.

3.3.1 Active Share and Tracking Error

Active share quantifies the difference between a fund's portfolio holdings and the benchmark portfolio in percent. Thus, information on portfolio holdings is needed. For the 38 funds in my sample, information about the portfolio weights is gathered through the funds' prospectuses and the Bloomberg database. The portfolio weights of the OSEFX are collected directly from Oslo Stock Exchange's database. The OSEFX portfolio, with its corresponding weights, is presented in Appendix 1.

Ideally, active share should be calculated over a longer time-period. However, as it requires calculations on differences in every single stock in a fund's portfolio relative to the benchmark index, it is a highly time consuming procedure. Thus, I have only considered the portfolio holdings as of December 31st 2015. In support of this, Cremers & Petajisto claim that "the active share of an individual fund is extremely persistent over time" (Cremers & Petajisto, 2009, p. 4). That is, one observation of active share should be sufficient to portray a realistic picture of the true activity levels in Norwegian equity mutual funds.

Cremers & Petajisto arbitrary chose an active share of 60% as the threshold for a fund to be classified as truly active (Cremers & Petajisto, 2009, p. 13). However, their study was performed on the U.S. market, which includes a significantly higher number of stocks relative to the Norwegian market. In other words, it is easier for a U.S fund to differentiate their portfolio relative to funds investing in the Norwegian market. In fact, there were only 209 stocks listed on the OSE as of December 31st 2015[19], whereas there were 3169 listed on NYSE[20]. Hence, it is easier for a fund investing in the U.S. to achieve a higher active share, than for a fund investing in Norway. The threshold of 60% thus seems high, and I would like to reduce it for this study. An intuitive threshold would be 50%. With an active share of 50%, the fund still has more active stock positions than passive, and it should be sufficient for a fund investing primarily in Norwegian stocks to be classified as active. That is, I will proceed with an active share of 50% as the threshold for an active fund in this study.

The tracking error is calculated as the standard error of the difference in return between a given fund and the benchmark index. Similarly to the active share, it is a time consuming task to calculate the tracking

[19] http://www.oslobors.no/Oslo-Boers/Statistikk/Fakta-og-noekkeltall/2015-Fakta-og-noekkeltall-desember-2015 - downloaded 17.08.2016
[20] http://www.nasdaq.com/screening/companies-by-industry.aspx?exchange=NYSE – downloaded 17.08.2016

error for 38 funds. Hence, due to time constraints, I have downloaded the tracking error of the funds in my sample directly from the Bloomberg database. Cremers & Petajisto used a tracking error of 6% as the threshold for a fund to be classified as truly active. I will proceed with their threshold in this study.

3.4 Funds' fees

The funds' fees are at the very core of the dispute on activity levels in actively managed funds. Both the government and the media have criticized actively managed funds of charging their investors too high fees relative to the product they deliver. Hence, it is a central aspect of this study to define the funds' fees. In this section, I will elucidate what the fees consists of and how the funds charge the fees to their investors.

As mentioned in section 3.3, there is a relationship between activity levels and the costs of investing in a mutual fund. The task of seeking out mispriced securities is resource intensive, which is why the more active funds should cost more than passive funds in theory. In practice, the fees investors pay to the funds are the costs of having their money invested in a mutual fund. The fees are the price the investors have to pay in order to have their assets managed by a professional portfolio manager. Often, the fees are referred in terms of a ratio, named the *Total Expense Ratio*, or simply TER. The TER is calculated as a fund's total costs divided by its total assets. Hence, the TER is a measure of a fund's total costs.

A mutual fund encounters a variety of costs, and the TER can be divided into sub-categories. The absolute majority of a funds' cost constitutes the management fees. These include bonuses to the fund managers and analysts[21]. How much the management fees constitutes of the total costs varies from fund to fund, but it tends to hover around 80% of the total costs. The remainder of the costs are transactions cost which the fund encounters through its trading activity. Examples are bid/ask spreads and brokerage fees. In addition, some mutual funds charges their investors entry and exit costs. As mentioned, the TER is dependent on activity levels and the most active funds tend to have an annual TER around 2%. The polar opposite of active funds, the index funds, tends to have an annual TER around 0.10 – 0.20%. The average annual TER of the 38 funds in my data sample is 1.44%, and ranges from 0.28% to 2.50% annually.

The TER is often posted in annual terms. However, in practice, the TER is deducted daily from the funds' end-off-day returns. That is, if a fund has a daily return of 1% before costs, 1/365 of the annual TER is deducted from the daily return. The ultimate return the investor obtains is thus the after costs return, also known as net returns. Thus, in terms of performance, the TER must be compensated through outperformance in order for the fund to deliver abnormal returns to their investors. The return before

[21] https://www.fidelity.com/learning-center/investment-products/mutual-funds/what-are-mutual-funds - downloaded 10.08.2016

deduction of costs, or gross return, illustrates the fund's actual performance, while the net returns are the ones relevant for the investors, as this is the investors' actual return on their investments.

The TERs in this study is obtained directly from the Morningstar database and the funds' prospectuses. For the performance tests, the funds' net asset values were downloaded from *Datastream*. That is, the fees were already deducted from the data. In order to obtain data on the funds' gross returns, I added back the funds' respective fees. Ideally, the funds' fees should be measured throughout the entire time period. However, there are no data available on historical fees. Hence, I have assumed that the fees were constant throughout my sample period. This is a simplification; however, it is in line with previous studies on mutual funds' fees. Amongst others, both Skålebråten (2013) and Norstein & Varran (2015) assume constant fees in their studies on the Norwegian market.

3.5 Single-Index Models

There are several components of the single-index models that needs to be collected and calculated. In the sub-sections below, I will present the methodology behind the performance measures included in this study.

3.5.1 Rate of Return

Both the Jensen regression and Treynor & Mazuy's market timing model considers excess returns, thus, the rate of return for each individual fund needs to be calculated. As mentioned in section 3.1.2, the end-of-month NAVs for the 10-year period is downloaded from Datastream. Moving from NAVs to rate of returns is a simple procedure, using the formula for geometric returns:

$$Geometric\ Returns = \ln(\frac{NAV_{i,t}}{NAV_{i,t-1}})$$

Where:
Ln is the natural logarithm
NAV_i is the net asset value for fund $_i$

In traditional portfolio evaluation, there are two conventional methods of calculating rate of return; arithmetic and geometric returns. Arithmetic returns tend to be preferred when the data is independent from each other, and "provides an unbiased estimate of the *expected* future return" (Bodie et al., 2014, p. 131). Investment returns are not independent from each other, and are backward looking in nature. If an investor loses money the first month, he will have a smaller capital base to generate returns of the next month. Hence, geometric returns tend to be preferred when working with historical returns as it provides a more realistic estimate of the actual returns. The geometric returns calculations are applied to both the individual funds and the benchmark index.

3.5.2 Risk-free rate

Another important component of the single-index models is the risk-free rate. As I am working with excess returns, the risk-free rate is deducted from both the individual funds' returns and the return on the market portfolio. In traditional investment literature, investors who buy stocks have an expected return in mind over the time period they hold the stock in their portfolio. However, the actual return they make on their stock position may vary widely from their expected return. This is where the risk aspect of investments is introduced. The risk of an investment is viewed in terms of the variance in actual returns in respect to the expected return (Damodaran, 2008, p. 3). For a risk-free investment, there will be no variance in actual returns in regards to the expected return, and the actual returns will always equal the expected returns.

In reality, there is no such thing as a risk-free investment. Hence, a proxy is needed for the risk-free investment. It is acknowledged that government bonds from solid and stable economies are the closest investment product to being risk-free, and is thus used as the risk-free component in single-index models. This is because the expected return of a highly rated government bond is (almost) always equal to the actual return, thus there is marginal risk involved (Damodaran, 2008, p. 3).

For the Norwegian market, it is common to apply the 3-month Treasury bill as the proxy for risk-free securities. This is the most frequently traded government bond on the OSE, and is thus the most appropriate candidate. I have chosen to apply the same risk-free proxy in my study. This is in line with previous studies on the Norwegian market, such as that of Sørensen (2009) and Skålebråten (2013). I have downloaded data on the 3-month Treasury bill from Datastream for my 10-year time period. The monthly risk-free rate, based on the 3-month T-bill, is calculated using the continuously compounded approach:

$$Monthly\ Riskfree\ Rate = (1 + r_t^{3M})^{\frac{1}{12}} - 1$$

3.5.3 Information variables for a time-varying beta

As discussed in section 2.5, a major simplification with the traditional single-index models is the assumption of a stable risk-level over time. Hence, I will follow Ferson & Schadt's approach of introducing a time-varying beta in my performance regressions. By applying publicly available information variables on dividend yields, interest rates and risk-free rates, I should obtain a more realistic risk estimate in my regressions.

Only three of the five original information variables Ferson & Schadt introduced were deemed statistically significant. Hence, only the three significant information variables will be included in the performance regressions in this study. The information variables in question are the lagged measure of the slope of the term structure, the lagged dividend yield and the lagged risk-free rate. The major challenge is to find the Norwegian equivalents of the three information variables. There are few studies on the Norwegian market where Ferson & Schadt's conditional performance models have been applied. However, Skålebråten (2013) followed their approach in his study on the Norwegian mutual fund industry. In his approach, he used the difference between the monthly yield of a long-term Norwegian government bond and a frequently traded short-term bond as the slope of the term structure (Skålebråten, 2013, p. 36). In fact, he used the 10-year government bond and the 3-month NIBOR[22]. The term structure is a financial term for the expectations of monetary policy decisions, or simply how the interest rates are expected to fluctuate in the foreseeable future. Naturally, they are expected to fluctuate within a certain range, as it is highly uncommon for interest rates to suddenly take a plunge or skyrocket. Norway is a small financial market, with a limited number of tradable instruments to indicate interest rate levels. Hence, the most suitable bond that can constitute an upper limit in this expected range is a long-term bond, as these tend to have a higher yield because of the increased uncertainty and risk associated with long-term horizons. Thus, a 10-year government bond is a suitable instrument for this upper limit. The lower limit in the range will consist of a short-term bond, as these have lower yields. Here, the 3-month NIBOR is a frequently traded and suitable candidate. Finally, to determine the actual range, the difference between the yield of the long-term and short-term bond is calculated and lagged by one month.

Furthermore, Skålebråten used the lagged dividend yield of his benchmark index as the second information variable (Skålebråten, 2013, p. 36). As I have chosen the OSEFX as my benchmark index (see section 3.2), I have proceeded with the same approach and lagged the dividend yield of the OSEFX by one month. Finally, for the risk-free rate, the same risk-free rate applied in section 3.5.2 has been lagged by one month. By combining the three mentioned information variables into a vector and added them to my performance models, I will obtain a time-varying risk-level of my regression estimates.

[22] Stands for Norwegian Interbank Offered Rate.

4.0 Actively Managed Equity Mutual Funds

As equity mutual funds are the very substance of this study, it is imperative to provide a clear definition of what they are and what they do. In this section I will outline how equity mutual funds operate, their characteristics, and how they are regulated. Moreover, I will elucidate the benefits of investing in actively managed equity mutual funds, and why investors traditionally choose active funds over passive funds. Finally, I will briefly discuss the major drivers behind the increase in popularity of funds, such as financial and technological innovation along with human behavior.

4.1 Characteristics and operations

A mutual fund can be defined as an investable product and an investment strategy combined into one product. In practice, a mutual fund is composed of a pool of funds provided by its investors, to which it can invest in all varieties of financial instruments. The most popular financial instruments among mutual funds are stocks, bonds, and money market instruments[23]. The mentioned pool of funds invested in securities, is commonly referred to as the fund's portfolio. An important aspect of mutual funds is the fact that anyone can invest in them. The typical investor can be anything from a private person, small or large corporations, trusts and even other mutual funds.

When an investor is looking to invest in a mutual fund, he must pay a price in order to obtain a share in the mutual fund's portfolio. This price for a share is commonly referred to as "*Net Asset Value*", or simply *NAV*. The NAV fluctuates on a daily basis, and is determined by the total value of the portfolio at the end of a business day divided by the fund's current number of outstanding shares[24]. The majority of mutual funds, including the ones under scrutiny in this study, are open-end mutual funds. An open-end fund is obligated to buy back the shares of any investor at the end of the business day, priced at the NAV at that point in time. In other words, when investing in open-end funds, the investor can enter and exit the fund whenever he feels the need for it.

Based on the reasoning in section 3.2, and thus the delimitations in regards to the benchmark index, this study only considers equity mutual funds with a domestic mandate. Equity mutual funds is a sub-category of mutual funds that primarily invests in stocks. In fact, an equity fund is required to invest at least 80% of its capital in equities (Skålebråten, 2013, p. 11). When we speak of equity mutual funds with a domestic mandate, it implies that the equity mutual fund primarily invests in stocks from its domiciled country. In Norway, domestic equity mutual funds are required to invest at least 80% of their capital in domestic

[23] https://www.fidelity.com/learning-center/investment-products/mutual-funds/what-are-mutual-funds - downloaded 10.08.2016 14:45
[24] https://www.fidelity.com/learning-center/investment-products/mutual-funds/what-are-mutual-funds - downloaded 10.08.2016 15:20

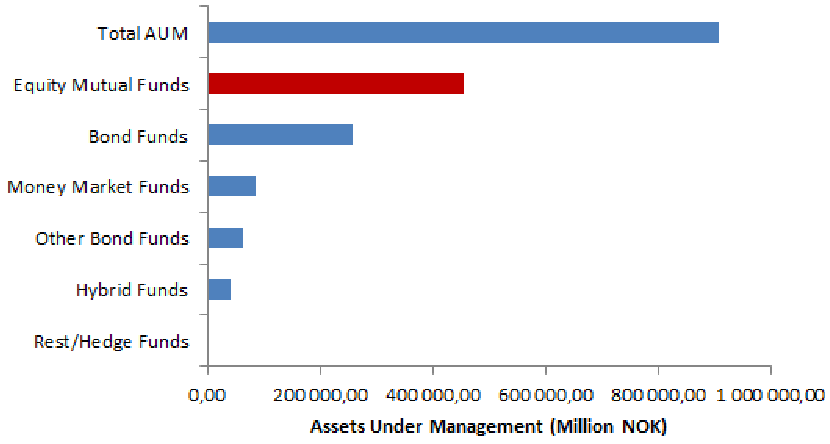
equities. Equity mutual funds can be further divided into the following sub-categories (Dine Penger, Nr8/2016. p. 37):

- **Actively managed:** The fund manager actively seeks out companies that are mispriced (micro forecasting). Furthermore, the manager actively seeks out entire sectors or industries that he/she believe will perform better than the market as a whole. Finally, the fund manager is actively rebalancing the portfolio based on anticipated trends in the market (macro forecasting). Due to the fact that information gathering is resource intensive, and their portfolios require constant monitoring, actively managed funds are relatively expensive compared to the alternatives.
- **Passively managed:** Is loosely copying a relevant benchmark index, without completely mimicking its portfolio. Hence, they rebalance their portfolios less frequently than actively managed funds, and are thus cheaper.
- **Index funds:** Is mimicking the relevant benchmark index exactly by holding the exact same portfolio of stocks as the benchmark. Thus, index funds guarantees the return you would get by holding the market portfolio less the costs. Mimicking a benchmark index involves a low trading frequency and requires almost no monitoring, and they are thus the cheapest among the equity mutual funds.

Equity mutual funds are the most popular funds among investors in Norway. Figure 4.1 presents a graphical illustration of the "*assets under management*" (AUM) for different types of funds domiciled in Norway in 2014. As you can see, approximately 50% of all assets in Norwegian funds are being managed by equity mutual funds[25]. As mentioned in section 3.1, according to the Norwegian Fund and Asset Management Association there are 407 equity mutual funds domiciled in Norway. Of those, 78 are either actively or passively managed equity mutual funds with a domestic investment mandate[26]. That is, only 16.45% of the available equity mutual funds in Norway are investing at least 80% of their assets listed on the OSE. However, due to the importance of having a suitable benchmark index, as described in section 3.2, I will proceed with the domestic equity mutual funds.

[25] http://www.ssb.no/bank-og-finansmarked/statistikker/vpfond/aar/2015-09-11#content – downloaded 11.08.2016
[26] http://vff.no/historisk-statistikk - downloaded 10.08.2016

Figure 4.1: Assets under management in the Norwegian fund market in 2014. Source: SSB.no (2016)



As Norway is a member of the European Economic Area (EEA), most of their funds are regulated by the same regulations as other funds in the EU. The current directive that governs the European investment fund market is the *Undertakings for Collective Investment in Transferable Securities Directives*, commonly referred to as the UCITS [27]. The UCITS is a thorough and intricate directive, regulating almost every single aspect of a European investment fund's operations. However, as this study only focuses on actively managed equity mutual funds' portfolio holdings, I will only discuss the aspects of the UCITS that directly affects this area of their operations.

One of the most important implications of the UCITS is the fact that it ensures a high degree of investor protection through legislations that imposes a minimum level of diversification of the funds' portfolio holdings. In order to ensure some degree of diversification, Article 52 §2 of the UCITS state that a fund must invest in at least 16 different securities. In addition, the UCITS imposes a rule which is often referred to as the "5/10/40-rule". This specific rule states that one security cannot exceed 10% of the fund's total value. Moreover, for securities accounting for more than 5% of the fund's total value, these aggregated cannot exceed more than 40% of the fund's total value (Skålebråten, 2013, p. 12). Apart from these rules, the UCITS also states that a fund can only invest 10% of its value in unlisted securities, and only 20% of a fund's value can be invested within the same industry.

4.2 Benefits of active fund management

On paper, active fund management provides several benefits for an investor. For a small fee, a person with no financial insight can get access to professional portfolio management. An investor would constantly have his portfolio monitored and analyzed by a professional and experienced trader, working with

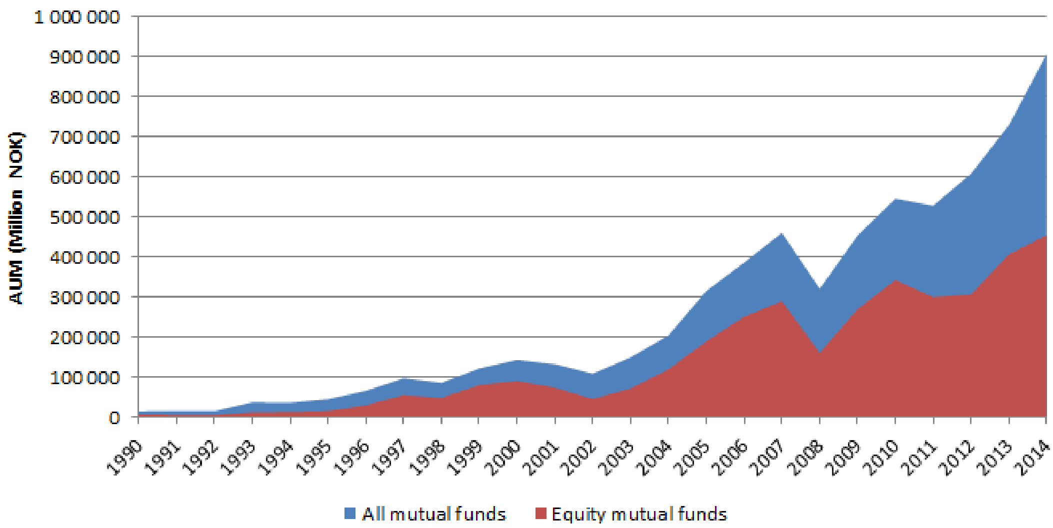
[27] http://ec.europa.eu/finance/investment/ucits-directive/index_en.htm - downloaded 10.08.16

appropriate technological resources. More importantly, by investing in active funds, anyone can get access to portfolio diversification and access to global markets, which would induce severe trading costs if it were to be done by a private investor. Taking into account that most equity mutual funds manage a portfolio consisting of dozens, even sometimes hundreds of stocks, it would not be feasible to replicate it with an average private investor budget. Hence, investing in actively managed funds is a cost-effective way of diversifying the risk involved with equity trading[28]. However, it is important to note that actively managed funds are considered a riskier investment than passively managed funds and that it might not be a suitable investment product for risk-averse investors.

4.3 Factors affecting the increase in fund popularity

There has been an explosive increase in fund investments in the Norwegian market during the last decades. According to Skålebråten (2013), the assets under management for Norwegian domiciled funds increased from 290 million NOK in 1982 to 608 557 million NOK in 2012 (Skålebråten, 2013, p. 10). In 2014, the number has increased to a staggering 907 581 million NOK[29], which entails an increase in AUM of 3129% in 32 years[30]. This increase is illustrated graphically in Figure 4.2 below. In the following two sub-sections I will try to pin point the main reasons why we have experienced this massive increase in fund popularity.

Figure 4.2: Increase in AUM for Norwegian funds (1990 – 2014). Source: Skålebråten (2013) & SSB.no



[28] https://www.fidelity.com/learning-center/investment-products/mutual-funds/what-are-mutual-funds - downloaded 10.08.2016
[29] http://www.ssb.no/bank-og-finansmarked/statistikker/vpfond - downloaded 11.08.2016
[30] Not accounting for inflation.

4.3.1 Financial and technological innovation

The recent increase in fund popularity is heavily affected by the financial innovation. Looking at Figure 4.2 above, you can see a massive increase in AUM from the beginning of the millennium until 2014. The financial innovation is affected by the technological innovation. Thus, I will discuss the financial innovation in light of the technological innovation in this section.

The rapid technological innovation has made it possible for literally anyone to trade whichever security they desire from anywhere in the world, as long as they are connected to the internet. In other words, there has been a major increase in the availability of financial instruments. Correspondingly with the increased availability, the demand for more specified instruments has risen. Nowadays, private and institutional investors are demanding a wide range of instruments, all with different investment horizons, target markets, strategies, risk-levels etc. Naturally, the Norwegian fund industry has benefited greatly from the technological innovation. This is especially evident when we look at the fact that in 1982, there was only one mutual listed on OSE (Gjerde & Sættem, 1991, p. 297), while there are close to 1400 mutual fund listed on OSE per 31.12.2015[31].

Another important aspect in the financial innovation is governmental deregulations. Governments have the ability sway the tax regulations in favor of alternative investment in financial markets. In Norway, the government reduced the tax level on capital gains from 28% to 27% in 2014[32]. In 2016, they continued their leniency towards capital gains and reduced the tax level to 25%[33]. When the tax is reduced on capital gains, an investor would receive a larger percentage of the surplus of his investments. Hence, the investor will have a larger incentive to invest in financial markets.

4.3.2 Human behavior and rationale

The final factor behind the increase in fund management that I would like to highlight is the human behavior and rationale behind fund investments. Nowadays, funds play an important role in household finance, especially in retirement planning. It is a well-known fact that people in the western world, and particularly in Norway, have experienced a significant increase in wealth during the last decades. Increased wealth tends to go hand in hand with a higher cost of living, which often has to be sustained during retirement. A study by Dybvik & Simonsen (2015) on Norwegian pension behavior identifies that Norwegians tend to prefer a smooth consumption through their lifetime (Dybvik & Simonsen, 2015, p. 18).

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[31] http://www.oslobors.no/markedsaktivitet/#/list/funds?page=28&ascending=true&sort=SECURITYNAME – downloaded 12.08.2016

[32] https://www.regjeringen.no/no/aktuelt/regjeringen-varsler-veksttiltak-for-nari/id725998/ - downloaded 12.08.2016

[33] http://www.skatt.no/2015/10/07/de-viktigste-nyhetene-i-statsbudsjettet-2016/ - downloaded 12.08.2016

That is, people will most likely incur the same level of costs of living in their middle ages as for their retirement years. The increased costs of living, along with increased longevity and government retirement plans that are not able to keep up, often ends in a negative sum game for certain individuals. Hence, people have started looking for alternative in retirement planning. Here, fund investments prevail as a tempting alternative due to the relatively low risk involved relative to other financial instruments.

Are Oust (2016) points to another reason as to why funds are becoming increasingly popular in Norway: the prevailing macro-economic environment (Dine Penger, Nr8/2016, p. 16). Nowadays, the key interest rate is at record low levels, while the inflation is relatively high. On December 31st 2015, the key interest rate was at 0.75%[34], while the inflation was at 2.30%[35]. In practice, this implies that Norwegians are experiencing negative real interest rates. When the average interest rate on savings accounts is hovering around 0.90%, it is obvious that the traditional saving method through bank deposits is unattractive. In fact, keeping your savings in a bank account with negative real interest rates means you are losing money. The only comparable alternative to a savings account is fund investments, because the risk is considered to be relatively low. Hence, Norwegians flock to funds in anticipation of a higher return on their savings.

Christian Lie (2016), points to the fact that we are currently facing the lowest global interest levels in modern time, which means that investors have to severely increase the risk-levels in their portfolio in order to obtain the same abnormal returns as earlier years. In 1995, one could obtain a 7.5% return on close to risk-free government bonds, whereas today that would be a pipedream (Danske Invest's weekly market report, week 33/2016, p. 1). The point made by Christian Lie further illustrates why people are flocking to alternative investment products such as actively managed funds.

[34] http://www.norges-bank.no/Statistikk/Rentestatistikk/Styringsgrente-manedlig/ - downloaded 12.08.2016
[35] http://www.norges-bank.no/Statistikk/Inflasjon/Indikatorer-for-prisvekst/ - downloaded 12.08.2016

5.0 Empirical Findings

This section presents the empirical findings of the tests on activity levels and the performance tests. Only the results from the individual tests are presented in this section of the study. In section 6, the results from this section are combined and analyzed in light of each other in order to elucidate the relationship between activity and performance. Furthermore, the practical implications of the findings will be discussed separately in section 6, and is thus not touched upon in this section.

5.1 Active Share

According to the reasoning in section 3.3, a fund should obtain an active share of 50% or higher in order to be classified as actively managed. In other words, at least half of a given fund's portfolio holdings must differ completely from the benchmark portfolio for a fund to be deemed actively managed. Given the selection criteria of only including self-proclaimed actively managed funds in this study, all of the 38 funds in my data sample should obtain an active share above this threshold by default. However, as the results in Table 5.1 below illustrates, the average active share in my sample is 46.56%, indicating that the average fund is not differentiating their portfolio holdings enough according to Cremers & Petajisto's definition. For a full view of the active share calculations for the individual funds, please refer to Appendix 2.

Table 5.1: Summary of Active Share Calculations. Source: Own creation

Benchmark	# of funds	Average active share	# of funds with active share > 50%	# of funds with active share < 50%
OSEFX	38	46.56%	14	24

Table 5.1 presents a summary of the active share calculations. Column 1 indicates the benchmark portfolio to which the respective funds' portfolio holdings are compared, while column 2 indicates the number of funds in the sample. Column 3 illustrates the average active share for the funds in the sample. Column 5 illustrates the number of funds in the sample who is truly active, while column 6 illustrates the number of funds that are self-proclaimed actively managed, but are in truth passively managed.

In fact, only 14 of the total 38 funds obtain an active share above 50%, which indicates that only 36.84% of the self-proclaimed actively managed funds in the data sample truly delivers the product they charge their investors for. These results must be deemed disappointing for the actively managed equity mutual fund industry, and supports the Norwegian government and media's recent criticism of the industry.

One of the more interesting observations from Cremers & Petajisto's original study was the fact that the smaller funds, in terms of assets under management, tend to obtain a higher active share than the larger funds (Cremers & Petajisto, 2009, p. 4). Unfortunately, they do not discuss any reasons as to why the smaller funds tend to obtain a higher active share than the larger funds. However, an intuitive explanation might be that smaller funds tend to be younger, and in order to attract investors they need to outperform to a larger extent than the more established and mature funds. It is a well-known fact in the financial world that the potential for higher returns is related to increasing the overall risk in one's portfolio. Hence, the smaller funds might diversify their portfolios to a larger extent than more mature funds in order to obtain a higher abnormal return, and thus obtain a higher active share.

Looking at Table 5.2 and Table 5.3 below, which portrays the 10 funds with the highest active share and the 10 funds with the lowest active share along with their respective AUMs, we see that Cremers & Petajisto's observation might also be true for the Norwegian market. The average AUM is indeed more than twice as high for the bottom 10 funds than for the top 10 funds. However, looking past the average numbers we obtain a different picture of the situation. Focusing on the individual funds instead of average numbers, the tables present a more ambiguous picture; the second *smallest* fund by AUM, *Danske Invest Norge I,* is actually the seventh *least* active fund in the sample. Moreover, the sixth *largest* fund by AUM, *Nordea Norge Verdi*, is actually the ninth *most* active fund in the sample. Further emphasizing this point, *DNB Norge III*, which is the sixth *smallest* fund by AUM, is also the sixth *least* active fund. As the reader would note by now, even though Cremers & Petajisto's findings on fund size relative to activity levels might hold water on average, it does not appear to work as a rule of thumb in the Norwegian market. An unknowing investor looking to invest in Norwegian actively managed equity mutual funds does seem to face a certain risk of receiving passive performance instead.

Table 5.2: Top 10 active share w/ AUM, ranked from highest to lowest. Source: Own creation

Fund	Active Share	AUM (NOK)	Ranking by AUM
DNB SMB	91.77%	645 286 000	18
Storebrand Vekst	78.61%	624 036 000	19
Danske Inv. Norge Vekst	76.70%	22 453 000	38
Pareto Investment Fund A	70.61%	441 983 000	24
Holberg Norge	70.36%	508 750 000	22
Pareto Aksje Norge - A	67.79%	1 149 583 000	13
Forte Norge	65.66%	32 103 000	36
Nordea Norge Pluss	61.45%	277 826 000	29
Nordea Norge Verdi	59.95%	3 367 515 000	6
Fondsfinans Norge	59.20%	1 124 845 000	14
Average Top 10	**70.21%**	**819 438 000**	

Table 5.3 Bottom 10 active share w/ AUM, ranked from highest to lowest. Source: Own creation

Fund	Active Share	AUM (NOK)	Ranking by AUM
Danske Inv. Institusjon II	31.61%	949 817 000	16
Danske Invest Norge II	31.46%	352 584 000	27
Danske Invest Norge I	31.22%	28 786 000	37
Danske Inv. Institusjon I	30.95%	472 762 000	23
DNB Norge IV	30.62%	319 307 000	28
DNB Norge III	30.61%	118 923 000	33
DNB Norge	30.61%	7 070 638 000	1
KLP Aksjenorge	28.69%	4 983 431 000	2
Storebrand Norge I	25.76%	4 506 200 000	4
Pluss Markedsverdi	25.42%	134 733 000	32
Storebrand Aksje Innland	19.62%	1 197 488 000	12
Average Bottom 10	**28.78%**	**1 830 424 455**	

5.2 Tracking Error

As discussed in section 2.1.1, the tracking error quantifies the risk-levels within a fund by differentiating the volatility between a portfolio return and the benchmark return. Despite the fact that the measure has been criticized for being too imprecise, I have included the tracking error in order to detect the individual funds' investment strategies. In other words, I will not rely completely on the tracking error on its own. However, by combining the tracking error and the active share, I am able to identify the individual funds' investment strategies. Of most importance for this study, the combination of tracking error and active share makes it possible to single out potential closet-indexing funds, which are self-proclaimed actively managed funds delivering a highly passive product. Please refer to section 2.1.3 for a more in-depth discussion on this area. Furthermore, with regards to the legal dispute presented in the introduction, it is the closet-indexing funds facing legal actions from the Norwegian government. Table 5.4 below presents the summary findings from the tracking error, while Table 5.5 and 5.6 presents the ten funds with the highest tracking error and the ten funds with the lowest tracking error respectively.

Table 5.4: Summary findings tracking error. Source: Own creation

Benchmark	# of funds	Average tracking error	# of funds with tracking error > 6%	# of funds with tracking error < 6%
OSEFX	38	6.16%	14	24

Table 5.4 presents the summary findings of the tracking error measure. Column 1 indicates the benchmark to which the respective funds' volatility are compared, while column 2 indicates the number of funds in the sample. Column 3 illustrates the average tracking error for the funds in the sample. Column 5 illustrates the number of funds in the sample who is truly active, while column 6 illustrates the number of funds that are self-proclaimed actively managed, but are passively managed in reality.

Remembering from section 3.3.1, a tracking error above 6% indicates an actively managed fund. As we can see from Table 5.4 above, the average fund in my sample obtains a tracking error of 6.16%. That is, according to this measure of activity, the average fund in the data sample is truly actively managed. In line with the active share measure, the tracking error identifies 24 self-proclaimed actively managed funds as being passively managed in reality. The fact that the two measures identifies the same number of passively managed funds is surprising as they base the measure of activity levels on two different aspects; the active share is based on differences in portfolio holdings, while the tracking error is based on differences in volatility. On the other hand, as they utilize the same benchmark reference, the findings might be expected to be somewhat similar across the same data sample on aggregate levels.

The majority of the funds in the "top/bottom 10" in Table 5.5 and 5.6 below differ from the "top/bottom 10" from the active share measure. Only *DNB SMB, Storebrand Vekst, Holberg Norge* and *Danske Invest Vekst* are present in the top ten for both measures. Similarly, *Storebrand Norge I, DNB Norge, DNB Norge III, DNB Norge IV, Storebrand Aksje Innland* and *Pluss Markedsverdi* are present in the bottom ten funds when it comes to both active share and tracking error. When a fund is classified as either active or passive across two different tests, the evidence obtained is stronger. However, as discussed above and in section 2.1, I will put more emphasize on the active share measure because of the tracking error's shortcomings. In this study, the results from the tracking error will only be analyzed together with the results from the active share measure. For a full overview of the individual funds' tracking error, please see Appendix 2.

Table 5.5: Top 10 tracking error funds, ranked from highest to lowest. Source: Own creation

Fund	Tracking Error
Storebrand Norge	15.45%
DNB SMB	12.25%
Storebrand Vekst	11.42%
Danske Invest Norge Vekst	10.97%
Odin Norge C	10.00%
Pareto Aksjo Norge - A	9.45%
Holberg Norge	8.42%
Nordea Norge Verdi	7.99%
Landkreditt Norge	7.66%
Alfred Berg Gambak	7.58%

Table 5.6: Bottom 10 tracking error funds, ranked from highest to lowest. Source: Own creation

Fund	Tracking Error
Storebrand Norge I	3.99%
Nordea Norge Pluss	3.85%
DNB Norge	3.76%
DNB Norge III	3.74%
DNB Norge IV	3.74%
Storebrand Aksje Innland	3.50%
Pluss Markedsverdi	3.29%
Carnegie Aksje Norge	3.24%
Nordea Kapital	2.73%
Nordea Avkastning	2.63%

5.3 Micro forecasting abilities

Identifying fund managers who are able to display micro forecasting abilities would be of great interest to any investor. By successfully identifying and picking underpriced stocks over an extended period of time, a fund is more likely to deliver abnormal returns to their investors. By performing a Jensen regression on the data sample, and thus quantify the abnormal return for each fund, it is possible to obtain evidence of superior micro forecasting abilities among the fund managers in actively managed Norwegian equity mutual funds. Conversely, I am also able to identify if there are fund managers that consistently pick overpriced stocks, a phenomenon often referred to as inferior micro forecasting abilities, which is a highly unattractive trait from an investor's point of view. Later in the study, I will compare the potential micro-forecasting abilities with the activity levels, to investigate whether there is a correlation between the level of activity and micro-forecasting abilities. As explained in section 2.4.1, the coefficient of interest in a Jensen regression is the alpha. Hence, for the Jensen regression there are five potential scenarios:

Table 5.7: Jensen's alpha scenarios. Source: Own creation

Scenario	Interpretation
1. Insignificant α = 0	Neutral performance: no micro forecasting abilities
2. Insignificant α > 0	Overperforming benchmark: no micro forecasting abilities
3. Insignificant α < 0	Underperforming benchmark: no micro forecasting abilities
4. Significant α > 0	Overperforming benchmark: superior micro forecasting abilities
5. Significant α < 0	Underperforming benchmark: inferior micro forecasting abilities

As Table 5.7 indicates, in terms of micro forecasting abilities one would be looking for significant alpha values, as this indicates presence of abilities. All single-index models included in this study are performed with a 95% confidence interval, which means that a t-value greater than 1.96 implies a significant alpha coefficient. Hence, a significant positive alpha coefficient indicates superior micro forecasting abilities with 95% certainty. An insignificant alpha coefficient, on the other hand, only indicates whether a fund is outperforming or underperforming relative to the benchmark index and refers to the potential outperformance/underperformance as luck or bad luck respectively.

This study measures the micro forecasting abilities in two dimensions: for traditional (unconditional), stationary risk levels and for time-varying (conditional) risk-levels. Both dimensions are presented in the following sub-sections. In addition, the Jensen regression is applied on both the funds' net returns and gross returns. The net returns are of particular interest for the investors, as it is the actual return they receive on their investments. The gross return, on the other hand, illustrates the funds' performance from a market efficiency point of view. That is, the gross return indicates whether a fund is able to outperform the benchmark index or not. By performing an analysis across both net and gross returns, I am able to conclude on whether a fund's outperformance is erased by the fund's fees, and thus if their outperformance ultimately benefits their investors. However, as this the main focus of this study is to discuss and conclude on the activity levels within the Norwegian equity mutual funds, the results from the single-index model tests will only be briefly discussed on their own. In other words, the results from the single-index models will be analyzed together with the activity levels identified in section 5.1, which is performed in section 6 of this study.

5.3.1 Stationary risk levels

Despite the argumentation for monthly data in section 3.1.2, the monthly alpha coefficients from the regression outputs are annualized into yearly figures. When working with time series of returns, it is considered "best practice" to present yearly figures, in contrast to weekly or monthly figures, as yearly figures are more intuitive and easier interpreted. Moreover, investors investing in mutual funds tend to have a longer time horizon on their investments, indicating that yearly alpha coefficients are better suited to the investors' need. In addition, all single-index model regressions in this study are performed using heteroscedasticity and autocorrelation consistent standard errors in order to ensure statistical validity and robustness. For a full overview of the Jensen's alpha coefficient for stationary risk levels, please refer to Appendix 3.

Figure 5.1: Frequency plot of net and gross Jensen's alpha. Source: Own creation

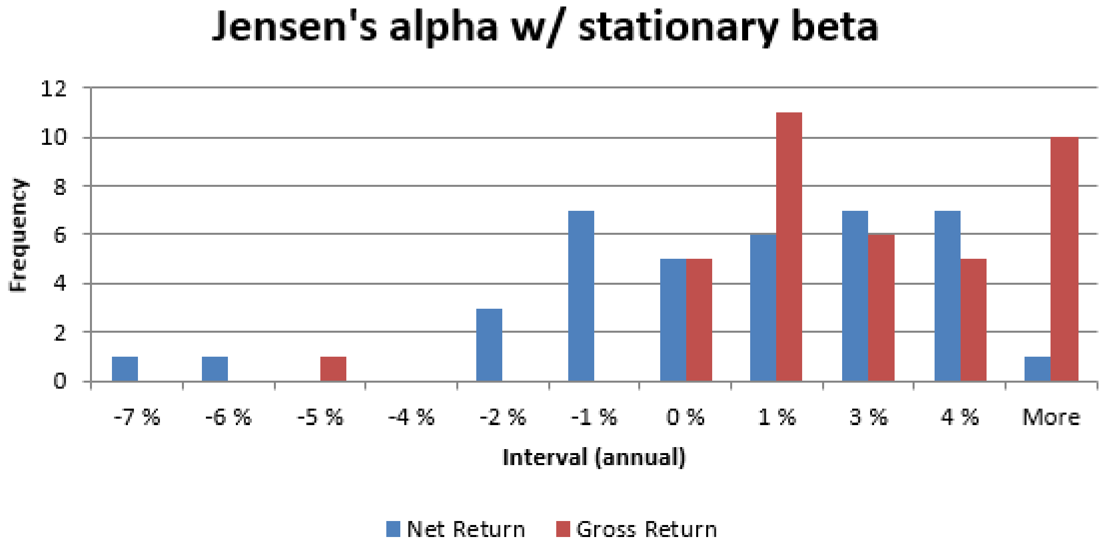

Table 5.8: Summary of Jensen regression w/ stationary risk levels. Source: Own creation

Benchmark	# of funds	Return Series	Average annual alpha	Significantly positive alpha	Significantly negative alpha
OSEFX	38	Net	0.239%	5	0
OSEFX	38	Gross	1.868%	14	0

Table 5.8 summarizes the results for the Jensen regression on both net and gross returns. Column 1 indicates which benchmark excess return the respective funds' excess returns have been regressed on, while column 2 indicates the number of funds included in the regression. Column 3 indicates the average annual alpha for the given regression. Ultimately, column 4 and 5 indicates the number of funds with a significant positive and significant negative alpha coefficient with a 95% confidence interval respectively.

5.3.1.1 Net returns

From the frequency plot in Figure 5.1 above, it is evident that the annual net alpha coefficients in the sample are skewed towards the right, which is preferable from an investor perspective. More specifically, as Table 5.8 above illustrates, the average annual alpha for the data sample is 0.239% when looking at the funds' net returns. That is, the average fund is outperforming the OSEFX benchmark by 0.239% each year after deduction of fees. Hence, the average investor would receive 0.239% more on his investment per year if he invested in an actively managed equity mutual funds, rather than passively managed index-tracking funds. The major selling point of actively managed funds is the potential of outperforming the benchmark and thus receiving abnormal returns on investments, and the aggregate results presented in Table 5.8 appears positive for the industry. More interestingly, the Jensen regression identifies five funds with a significant positive alpha coefficient. In other words, there are five funds in the data sample where I find statistically significant evidence of the fund managers exhibiting superior micro forecasting abilities. That is, by continuously identifying and picking underpriced stocks, the fund managers are able to maximize the returns on their portfolios and add value for their investors. At the same time, there is no evidence of inferior micro forecasting abilities among the funds in the sample, which further strengthens the positive impression of the results.

However, it is important to not get blinded by these seemingly positive results. An interesting observation occurs if I remove the five significantly positive alpha funds from the sample. In that case, I end up with a negative average net alpha. In fact, as illustrated in Table 5.9 below, I end up with an average annual net alpha of -0.205%, which actually indicates average underperformance after fees. Taking into account that among 38 funds, the average net performance of 33 of the funds in the sample is below that of the benchmark index indicates that an average investor has a high probability of investing in an actively managed fund and receive a product that is even inferior to passively managed funds.

Table 5.9: Scenario excluding significant alpha funds. Source: Own creation

Scenario	# of funds	Average annual alpha	Interpretation
Excluding significant alpha funds	33	-0.205%	Average Underperformance

Secondly, taking into account that the reason actively managed funds are more expensive than passively managed funds is because they actively seek out underpriced stocks, one should expect a higher number of funds with a significant positive alpha. Based on the definition of Jensen's alpha, when only five fund managers exhibit superior micro forecasting abilities, the remaining 33 funds' outperformance/underperformance is due to luck/bad luck. For an investor, this implies that there is a high probability of randomly investing in a fund which performance is due to luck. The five funds displaying superior micro forecasting abilities are presented in Table 5.9 below.

Table 5.10: Funds with superior micro forecasting abilities, net returns. Source: Own creation

Fund name	Net Return: Yearly α	Net Return: t-stat	β	Obs.	R^2 adj.
Danske Invest Inst. I	**0.0383****	**(3.02)**	0.91189	120	0.9680
Danske Invest Inst. II	**0.0377****	**(2.97)**	0.91004	109	0.9647
Danske Invest Norge II	**0.0342***	**(2.66)**	0.89666	120	0.9654
Danske Invest Norge I	**0.0255****	**(2.01)**	0.90527	120	0.9667
Pluss Markedsverdi	**0.0229***	**(2.39)**	0.91458	120	0.9821

** $p < 0.01$

* $p < 0.05$

Danske Invest is present with four of their total five funds in Table 5.10, with *Danske Invest Institusjon I* being the best performing fund with a significant positive alpha at the 1% level, indicating an average yearly outperformance of 3.83% after deduction of fees. A natural question that arises in terms of the five funds presented in Table 5.10 is; what are they doing differently from the rest of the funds? By looking at their respective portfolios, it is possible to identify what sectors they are primarily investing in, and thus see if the five funds' stock picking within the sectors might be the reason why they are performing better than the rest of the sample. The funds' portfolio holdings are publicly available information, and can either be found on the respective funds' webpages, or from a third-party database such as Bloomberg. All five of the funds in question are investing the majority of their assets in the seafood, financial and telecom industry, while they have relatively low portfolio weights in shipping and the petroleum industry. Shipping and petroleum is two of the major industries in Norway, and the absolute majority of the funds in the data sample have substantial portfolio holdings within these industries. Many of them hold the maximum portfolio holdings allowed with regards to the UCITS-regulations (see section 4.1). Identifying the exact reason why the five funds in Table 5.10 is performing better than the rest is challenging and the sector strategy is only one of multiple possibilities. It is important to remember that the Jensen regression only addresses the individual selection of stocks, and does not look into sector strategies specifically. However, the fact that all five funds' portfolio holdings are quite similar could imply that they are identifying and picking the correct underpriced stocks in specific sectors where underpriced stocks are more common, and thus have a larger growth potential than other sectors.

5.3.1.2 Gross returns

The gross return aspect of the Jensen regression is of particular interest when being compared to the net return regression. By doing so, it is possible to identify whether large portions of any outperformance and benefits from micro forecasting abilities are lost through the funds' fees. As mentioned in section 5.3, the gross return quantifies the actual outperformance, and thus illustrates whether actively managed mutual funds as an investment vehicle performs better than a passively managed alternative. The net returns, on the other hand, is the actual return the investors make on their investments. Hence, by analyzing the difference between the two, it is possible to identify how much of the abnormal return that is lost through fees.

Naturally, the average annual alpha of the gross return is higher than for the net returns, as I have added the TER from each individual fund to the net returns. From Table 5.8, we see that the average annual gross alpha is 1.868%, compared to 0.239% in the net return regression. In other words, the average fund in the data sample is outperforming the OSEFX benchmark, and thus a passively managed alternative, by 1.868% per year before deduction of fees. Another interesting observation is the fact that I am able to identify 14 funds with a significant positive alpha compared to the five funds in the net return regression. However, this is not a positive finding from the active fund industry's point of view, as it implies that for nine funds, the investors do not share in on the benefits of superior micro forecasting abilities. In fact, all benefits of the superior abilities are kept within the funds because the fees erase any potential benefits for the investors. The funds that benefit from superior micro forecasting abilities but not their investors are presented in Table 5.11 below.

Table 5.11: Funds w/ significant alpha before deduction of fees. Source: Own creation

	Gross Return				
Fund name	**Yearly α**	**t-stat**	**β**	**Obs.**	**R^2 adj.**
Handelsbanken Norge	**0.0503****	**(2.95)**	0.9533	120	0.9533
Alfred Berg Gambak	**0.0473***	**(2.13)**	0.91167	120	0.9106
Fondsfinans Norge	**0.0451***	**(2.23)**	0.90212	120	0.9246
Pareto Investment Fund A	**0.0418***	**(2.10)**	0.94362	120	0.9327
Pluss Aksje	**0.0393****	**(2.81)**	0.83734	120	0.9594
Alfred Berg Aktiv	**0.0318***	**(2.01)**	0.94154	120	0.9543
Carnegie Aksje Norge	**0.0277***	**(2.55)**	0.95732	120	0.9802
Nordea Kapital	**0.0240****	**(2.89)**	0.94871	120	0.9875
Nordea Avkastning	**0.0179***	**(2.24)**	0.95913	120	0.9884

**** $p < 0.01$**

*** $p < 0.05$**

The funds presented in Table 5.11 are funds that should be attractive to investors, as they do in fact possess micro forecasting abilities. Unfortunately, as the fees seemingly erase the initial benefits, they end up as unattractive funds for an investor in reality. It is important to note that these funds do in fact outperform the benchmark, but as the Jensen regressions on net returns identifies insignificant alpha coefficients for the funds in question, the outperformance only benefits the fund.

5.3.2 Time-varying risk levels

As mentioned in section 2.5 and 3.5.3, I am following Ferson & Schadt and Skålebråten's approach and applying a time-varying beta to the traditional single-index models, in an attempt to improve the traditional regression models' explanatory power. More specifically, the introduction of a time-varying beta might help control for omitted variable bias, and thus improve the regression models. In their study, Ferson & Schadt claims that if the risk is levels are kept constant, average performance might be confused with common time variations in risks and risk premiums (Ferson & Schadt, 1996, p. 425). The traditional performance models suffer from trying to ascribe superior fund performance to interpretation and use of readily available public information. However, stock prices should already reflect publicly available information according to the EMH. Hence, by adding the information variables, and thus a set of publicly available information on risk-levels, I hope to reduce some bias tied to publicly available information. Moreover, a time-varying beta portrays a more realistic picture as the macroeconomic environment is highly unpredictable and the risk is constantly changing.

Adding the time-varying beta does not change the interpretation of the alpha coefficient, which is still the coefficient of interest. However, I introduce a second aspect to the regression output: whether the traditional, static, regression models were improved or not. In order to determine if a model is improved, I adopt Skålebråten's F-test to investigate whether the three information variables are at any time jointly zero (Skålebråten, 2013, p. 40). If at least one of the information variables is different from zero, the introduction of a time-varying beta improves the traditional models, and the time-varying model will be preferred. The F-test applied in this study is defined as follows:

$$F = \frac{\frac{SSE_{Unconditional} - SSE_{Conditional}}{No.of\ extra\ terms}}{MSE_{Conditional}}$$

When the F-value exceeds the critical value of 5.682 for 100 observations, the traditional regression model is rejected, and at least one of the information variables add explanatory power to the model. For a full overview of the funds' regression outputs with a time-varying beta coefficient, along with their respective F-value, please refer to Appendix 4.

Figure 5.2: Frequency plot of net and gross Jensen's alpha. Source: Own creation

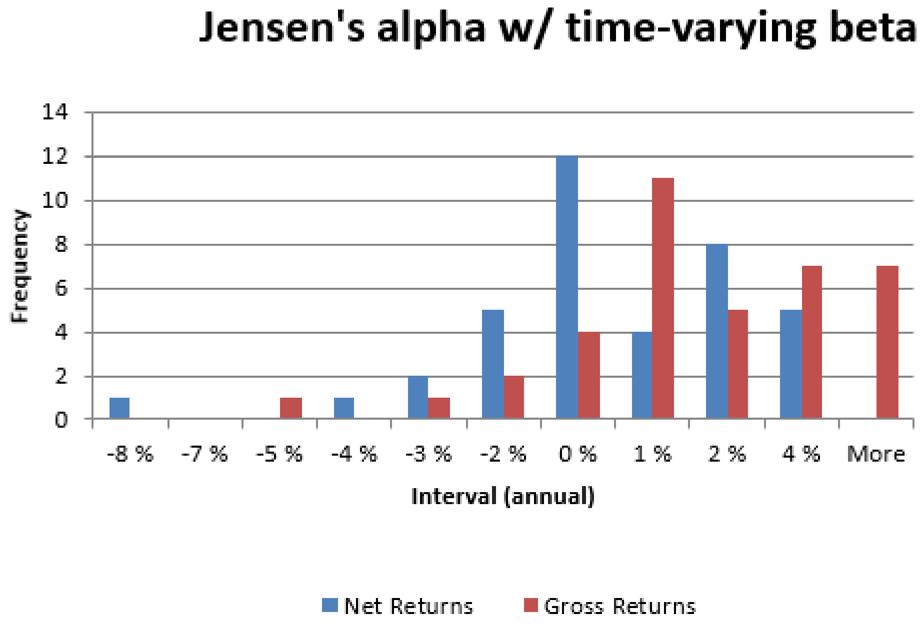

Table 5.12: Summary of Jensen regression w/ time-varying risk-levels. Source: Own creation

Benchmark	# of funds	Return Series	Average annual alpha	Signficantly positive alpha	Significantly negative alpha	# of models improved
OSEFX	38	Net	-0.253%	2	1	12
OSEFX	38	Gross	1.184%	10	1	12

Table 5.12 summarizes the results for the Jensen regression on both net and gross returns. Column 1 indicates which benchmark excess return the respective funds' excess returns have been regressed on, while column 2 indicates the number of funds included in the regression. Column 3 indicates the average annual alpha for the given regression. Column 4 and 5 indicates the number of funds with a significant positive and negative alpha coefficient with a 95% confidence interval respectively. Ultimately, column 6 indicates the number of models that were improved by introducing a time-varying beta coefficient into the regression.

5.3.2.1 Net Returns

From Table 5.12, it is evident that introducing time-varying risk levels severely punishes the alpha coefficients. The average annual alpha is estimated to -0.253% for the net return regressions, compared to an average net alpha of 0.239% in the static risk level scenario, which represents a decrease of 205%. The frequency plot in Figure 5.2 further illustrates this finding, where one can observe a larger portion of the funds obtain a net alpha estimate around 0% compared to the frequency plot in Figure 5.1. Furthermore, there are fewer funds with a net alpha skewed towards the right of the frequency plot, implying a lower average annual alpha estimate for the sample as a whole.

In terms of improving the explanatory power of the models, Table 5.12 indicates that 12 regression models were improved by introducing the time-varying risk-levels. That is, I was able to improve 31.58% of the traditional Jensen regression models. For the 12 funds, the time-varying regression estimates will be preferred, and the 12 funds in question are highlighted in Appendix 4.

The most startling finding presented in Table 5.12, is that I am now only able to identify two funds with superior micro-forecasting abilities. Interestingly, the two funds are *Danske Invest Institusjon I and II*, which were also identified as having superior abilities in the static beta regressions in section 5.3.1.1. This finding serves as a sign of quality towards to the portfolio managers of the two Danske Invest funds, as they seem to be able to be able to identify underpriced securities in both a static and a time-varying risk environment. In addition, there is now evidence of a fund with inferior micro-forecasting abilities, which is evident through a statistically significant negative net alpha. A significantly negative net alpha is highly unattractive to investors and a discouraging finding from the actively managed equity mutual fund industry's point of view. As Table 5.13 below illustrates, the negative alpha fund is *Holberg Norge*. In fact, after deduction of fees, the fund underperforms relative to the benchmark by a staggering 5.15% per year. It is hard to imagine how a fund with such poor performance is able to survive. A potential explanation to this is might be that the average investor is simply not aware of the net alpha, as the funds themselves tend to disclose their gross alpha in silence when they promote themselves. Furthermore, Table 5.13 show that all three funds have a F-value above the critical value of 5.682, which means that the regression outputs below are the preferred and most reliable estimates.

Table 5.13: Significant net alphas w/ time-varying betas. Source: Own creation

	Net Returns					
Fund name	**Yearly α**	**t-stat**	**β**	**Obs.**	**R^2 adj.**	**F-Value**
Danske Invest Inst. I	**0.0296***	**(2.21)**	0.90642	120	0.9694	**6.723***
Danske Invest Inst. II	**0.0270****	**(3.07)**	0.90812	109	0.9685	**6.723***
Holberg Norge	**-0.0515***	**(-2.61)**	0.86421	120	0.9021	**25.080***

*** p < 0.05**
**** p < 0.01**

5.3.2.2 Gross returns

Similar to the findings in the net return scenario, the introduction of a time-varying beta leads to a severe reduction in the average annual alpha across the sample. Compared to the static beta scenario presented in section 5.2.1.2, the average gross alpha is reduced from 1.868% to 1.184%. In other words, when the risk-levels are allowed to vary across time, the average outperformance is 0.684% less on an annual basis. Furthermore, the number of statistically significant outperforming funds is reduced from 14 to 10. I am also able to identify *Holberg Norge* as displaying significant inferior micro forecasting abilities, similar to the net return scenario in the previous sub-section.

Table 5.14: Funds w/ significant alpha before deduction of fees (conditional) Source: Own creation

	Gross Returns					
Fund name	**Yearly α**	**t-stat**	**β**	**Obs.**	**R^2 adj.**	**F-Value**
Handelsbanken Norge	**0.0538****	**(2.96)**	0.97861	120	0.9531	0.441
Alfred Berg Gambak	**0.0535***	**(2.26)**	0.89109	120	0.9105	1.036
Danske Invest Norge I	**0.0355****	**(2.73)**	0.94254	120	0.9690	**10.000***
Danske Invest Norge II	**0.0352****	**(2.69)**	0.93803	120	0.9683	**12.500***
Pluss Markedsverdi	**0.0250***	**(2.76)**	0.93896	120	0.9831	**7.879***
Pluss Aksje	**0.0234***	**(2.12)**	0.89024	120	0.9652	**21.552***
Carnegie Aksje Norge	**0.0219***	**(2.26)**	0.97684	120	0.9806	4.096
Nordea Kapital	**0.0177***	**(2.14)**	0.96988	120	0.9882	**7.959***

*** $p < 0.05$**
**** $p < 0.01$**

Similar to the reasoning in section in section 5.3.1.2 in the static risk level scenario, the funds listed in Table 5.14 above keep all benefits of superior micro forecasting abilities within the funds. Hence, the investors are not able to share in on the benefits, and any outperformance on net return level is regarded as luck according to the Jensen regression. Five of the funds listed in Table 5.14, obtain an F-value above the critical level, which implies that the time-varying beta improved their model and the time-varying risk-level model will be preferred for these funds.

5.4 Macro forecasting abilities

In addition to being able to predict micro movements in the markets, fund managers might be able to predict larger, fundamental market movements. These broader market movements are commonly referred to as macro movements, and concerns entire financial markets and sectors rather than individual securities. By successfully anticipating which direction the financial market is heading in the near future, fund managers can generate substantial excess returns on the market and thus benefitting their investors. In practice, macro forecasting is done by altering their portfolios according to the prevailing market conditions. Specifically, this means investing based on the individual securities' risk. In a booming market, a fund manager would strive to capture as much of the upswing as possible, by shifting his portfolio towards high-beta securities as these on average are more volatile and have more fluctuating price movements than low-beta securities. In a booming market, a high-beta security would, on average, have a higher price increase than a low-beta security, and by successfully altering their portfolios towards high-beta securities the funds will capture more of the upswing. Conversely, if the market is anticipated to fall, the fund managers will alter their portfolios towards low-beta securities as these tend to have less price decrease than high-beta securities. Hence, the overall decline in the market would not affect a low-beta portfolio to the same extent, and the fund would outperform in declining markets as well.

As mentioned in section 2.4.2, this study applies Treynor & Mazuy's market timing model in order to identify potential macro forecasting abilities among the funds in the data sample. In contrast to the Jensen regression, the coefficient of importance is the gamma, γ. From the theory section, we know that the gamma quantifies the slope of the characteristics line, which illustrates to what extent a fund is outperforming the benchmark index through its excess return. That is, the higher the gamma, the higher the outperformance relative to the benchmark is. Unfortunately, the gamma coefficient does not have the same intuitive interpretation as the alpha coefficient, and whether one fund's gamma coefficient is regarded as high or low depends on the coefficients of the rest of the sample. As this study only concerns evidence of macro forecasting abilities, there are three possible scenarios when applying Treynor & Mazuy's market timing model:

Table 5.15: Treynor & Mazuy scenarios. Source: Own creation

Scenario	Interpretation
1. Insignificant γ	No evidence of macro forecasting abilities
2. Significant $\gamma > 0$	Evidence of superior macro forecasting abilities
3. Significant $\gamma < 0$	Evidence of inferior macro forecasting abilities

As Table 5.15 illustrates, an insignificant gamma coefficient implies no evidence of macro forecasting abilities. However, a significant positive gamma indicates superior forecasting abilities. That is, a fund manager is able to continuously predict the overall market movements in the correct direction. A significant negative gamma does in fact imply that a fund manager is able to predict market movements, but continuously in the wrong direction. However, in reality this would be easily dealt with, as any rational fund manager would simply reverse his strategy when he became aware of it.

The Treynor & Mazuy model identifies micro forecasting abilities through its intercept, as well as the macro forecasting abilities. In this study, however, it is solely included for the macro forecasting abilities as the results from the already mentioned Jensen regression will be preferred for the micro forecasting abilities. On the other hand, it is interesting to see how the alpha values behave when I control for macro forecasting abilities. However, I will not comment on alpha values beyond how they react to the gamma coefficient. As with the Jensen regression, HAC standard errors have been applied to ensure statistical validity and robustness in the results, and I am conducting the analysis on an individual fund basis. Furthermore, due to way the Treynor & Mazuy model is compounded, it is indifferent between net and gross returns. Hence, only the net returns are analyzed in this section. In section 6, the macro forecasting abilities will be analyzed together with the activity levels identified above, in order to elucidate if there is a relationship between macro forecasting abilities and activity levels. The regression outputs from the macro forecasting abilities tests, both with static and time-varying beta, are presented in Appendix 5 and 6 respectively.

5.4.1 Stationary risk levels

Table 5.16: Summary of Treynor & Mazuy regression, w/ static beta. Source: Own creation

Benchmark	# of funds	Average annual alpha	Average gamma	Significantly positive gamma	Significantly negative gamma
OSEFX	38	-0.652%	0.372	12	2

Table 5.16 summarizes the results for the Treynor & Mazuy regression on net returns. Column 1 indicates which benchmark excess return the respective funds' excess returns have been regressed on, while column 2 indicates the number of funds included in the regression. Column 3 indicates the average annual alpha for the given regression, while column 4 indicates the average gamma coefficient of the sample. Ultimately column 5 and 6 indicates the number of funds with a significant positive and significant negative gamma coefficient with a 95% confidence interval respectively.

As Table 5.16 illustrates, the average annual alpha of the sample is reduced heavily after controlling for macro forecasting abilities. Compared with the average net alpha from the Jensen regression, it has been reduced from 0.239% to -0.652%. Hence, the average fund has moved from outperformance to underperformance relative to the benchmark. However, these findings are in line with previous literature; both Grant (1978) and Skålebråten (2013) identifies a drop in the average alpha when market timing is present in the performance model.

The most interesting finding from the alpha obtained from the Treynor & Mazuy regression, is the fact that I am not able to identify a single fund with both superior micro forecasting abilities and macro forecasting abilities present at the same time, which is evident from the regression output in Appendix 5. These funds would be highly attractive for investors, and this finding must be deemed disappointing from the fund industry's point of view. At the same time, I am not able to identify any funds with both significant negative alpha coefficients and significant negative gamma coefficient, which would be highly *unattractive* funds. However, this is not surprising, as such funds would most likely underperform to such an extent that they would become defunct within a short time span.

Looking at the average gamma coefficient, we see that it is positive on average. Furthermore, I am able to identify 12 funds displaying superior macro forecasting abilities that benefit their investors. Compared to the disappointing findings from the micro forecasting regressions, this is an uplifting finding for the Norwegian actively managed equity mutual fund industry. The 12 funds, and their respective gamma values, are presented in Table 5.17 below, ranked by their gamma coefficients from highest to lowest.

Table 5.17: Significant positive gamma coefficients w/static beta. Source: Own creation.

	Net Returns			
Fund name	**γ**	**t-stat**	**Obs.**	**R^2 adj.**
Forte Norge	**2.11689***	**(2.10)**	57	0.7711
DNB Norge Selektiv II	**1.68048***	**(2.45)**	60	0.8875
DNB Norge Selektiv III	**1.68039***	**(2.44)**	60	0.8877
DNB Norge Selektiv I	**1.67134***	**(2.43)**	60	0.8884
Landkreditt Norge	**0.60455****	**(4.02)**	114	0.9083
Pluss Aksje	**0.49318****	**(2.87)**	120	0.9676
Danske Invest Norge II	**0.27377***	**(2.62)**	120	0.9672
Danske Invest Inst. I	**0.26352****	**(2.81)**	120	0.9698
Danske Invest Inst. II	**0.26352****	**(2.81)**	120	0.9698
Pluss Markedsverdi	**0.26316****	**(2.64)**	120	0.9840
Danske Invest Norge I	**0.22702***	**(2.01)**	120	0.9680
Nordea Kapital	**0.18051***	**(2.10)**	120	0.9883

** $p < 0.01$
* $p < 0.05$

One fund stands out with particularly impressive macro forecasting abilities, namely *Forte Norge*. By successfully anticipating the overall market movements, they obtain a gamma coefficient that is 470% higher than the average alpha of the sample as a whole. The fact that *Forte Norge* obtains these results on their net returns implies that their investors are benefitting from the abilities. Looking at *Forte Norge's* adjusted R^2, however, it is slightly lower than the rest of the funds presented in Table 5.17. Hence, there might be factors affecting the macro forecasting abilities that are not included in the Treynor & Mazuy model, and the result is less reliable.

I am also able to identify two funds with the strange ability of constantly being able to predict the market movements in the wrong direction. As explained in the introduction of this sub-section, this is an unexpected finding, as any rational fund manager could simply reverse his strategy and thus possess superior macro forecasting abilities. On the other hand, some fund managers have other strategies than predicting macro movements and allocating their portfolios accordingly. For instance, a fund investing a particular segment of the market would be highly exposed to macro movements, and thus might be in danger of receiving a significant negative gamma coefficient by coincidence. The two funds in question are presented in Table 5.18 below.

Table 5.18: Singificant negative gamma coefficient w/ static beta. Source: Own creation

Fund name	Net Returns γ	t-stat	Obs.	R^2 adj.
Handelsbanken Norge	-0.22513*	(-2.41)	120	0.9541
Alfred Berg Gambak	-0.31694*	(-2.28)	120	0.9126

** $p < 0.01$
* $p < 0.05$

5.4.2 Time-varying risk levels

Table 5.19: Summary of Treynor & Mazuy regression, w/ time-varying beta. Source: Own creation

Benchmark	# of funds	Average annual alpha	Average gamma	Signficantly positive gamma	Significantly negative gamma	# of models improved
OSEFX	38	-0.309%	0.196	3	6	9

Table 5.19 summarizes the results for the Treynor & Mazuy regression on net returns. Column 1 indicates which benchmark excess return the respective funds' excess returns have been regressed on, while column 2 indicates the number of funds included in the regression. Column 3 indicates the average annual alpha for the given regression, while column 4 indicates the average gamma coefficient of the sample. Column 5 and 6 indicates the number of funds with a significant positive and significant negative gamma coefficient with a 95% confidence interval respectively. Ulitmately, column 7 presents the number of models improved by introducing a time-varying beta.

Introducing a time-varying beta to the Treynor & Mazuy regression impacted the explanatory power less than in the Jensen regression. As we can see, only 9 models, or 23.86% of the total models, were improved, which makes the time-varying Treynor & Mazuy regression less impactful than anticipated. As Appendix 6 illustrates when looking at the F-value, only the regression model on some of the funds identified with a significant negative gamma coefficient were improved. Hence, only the funds with significant negative gamma will be presented in this section, as the static beta model is preferred for the significant positive gamma funds. On aggregate levels, the time-varying beta seems to drag the average gamma coefficient downwards, with 0.196 compared to 0.372 in the static beta model. However, the low improvement of models makes this finding less reliable.

Furthermore, the time-varying beta model identifies six funds with inferior market timing abilities, compared to two in the static beta scenario. The increase in significant negative gamma funds when allowing the risk-levels to vary through time is in line with Skålebråten's (2013) findings on the Norwegian market. Moreover, he also identified a decrease in the average gamma coefficient. The funds identified with a significant negative gamma coefficient are presented in Table 5.20 below. As we can see, *Alfred Berg Aktiv, Odin Norge C, Pareto Aksje Norge A* and *Pareto Investment Fund A* obtain a significant F-value, implying that the time-varying beta model is preferred over the static beta model for these funds.

However, as the interpretation of the significant negative gamma is identical to the negative gamma coefficients identified in the static beta scenario, I will not comment on them any further.

Table 5.20: Significant negative gamma coefficients w/ time-varying beta. Source: Own creation

	Net Returns				
Fund name	**γ**	**t-stat**	**Obs.**	**R^2 adj.**	**F-value**
Alfred Berg Aktiv	**-0.39340***	**(-2.23)**	120	0.9558	**6.316***
Alfred Berg Gambak	**-0.56621****	**(-2.90)**	120	0.9127	1.072
Handelsbanken Norge	**-0.46804****	**(-2.63)**	120	0.9544	1.826
Odin Norge C	**-0.89105***	**(-2.09)**	107	0.8577	**12.688***
Pareto Aksje Norge A	**-0.81281***	**(-2.03)**	120	0.8596	**9.707***
Pareto Investment Fund A	**-0.63058***	**(-2.87)**	120	0.9355	**6.738***

**** $p < 0.01$**

*** $p < 0.05$**

6.0 Analysis and practical implications of findings

In this section the empirical findings from section 5 will be analyzed in light of each other. Firstly, the active share and tracking error will be combined in order to identify potential closet indexing funds that are under heavy scrutiny from the Norwegian government and media. Secondly, activity levels and performance, along with managerial abilities, will be analyzed in light of each other. That is, the results from the activity measures will be combined with the findings from the single-index models in order to elucidate whether there is a relationship between activity levels and skills. Ultimately, the activity levels will be analyzed together with the individual funds' TER in order to elucidate whether the relationship between activity and costs is according to theory. Throughout the section, the practical implications of the findings from the analysis will be presented from an investor perspective in order to highlight the importance of the findings from an investor's point of view.

6.1 Identifying investment strategies

In a study on true activity levels within actively managed funds, it is imperative to identify the individual funds' investment strategies. It is especially important to identify any closet-indexing funds. From section 2.1.3, we know that closet-indexing funds are funds that portray themselves as being highly active, but are in reality holding a portfolio approximately equal, or similar, to the passive benchmark. Hence, closet-indexing funds are highly misleading and accused of defrauding their investors.

By combining the findings on active share from section 5.1 with the findings on tracking error from section 5.2, I am able to create a two-dimensional classification of the funds in my data sample. That is, I am able to identify which funds engage in stock picking (micro forecasting), which funds engage in market timing (macro forecasting), which funds engage in both, and which funds engage in none of the already mentioned strategies. Based on the definition of the active share and the tracking error, by not engaging in either strategies and thus maintain a highly passive strategy, the fund will by default end up with a portfolio with high similarity to the benchmark's portfolio. The results of the combination of active share and tracking error, and thus the funds' identified investment strategies are presented in Table 6.1 below.

Figure 6.1: Identifying investment strategies. Source: Own creation based on Cremers & Petajisto (2009)

Active Share

Diversified Stock Picks	**Concentrated Stock Picks**
Nordea Norge Pluss	Alfred Berg Gambak
Storebrand Optima Norge	Danske Invest Norge Vekst
	Delphi Norge
	DNB SMB
	Fondsfinans Norge
	Forte Norge
	Holberg Norge
	Nordea Norge Verdi
	Pareto Aksje Norge A
	Pareto Investment Fund A
	Storebrand Vekst
Closet Indexing	**Factor Bets**
Carnegie Aksje Norge	Odin Norge C
Danske Invest Norge I	Storebrand Norge
Danske Invest Norge II	
Danske Invest Norske Aksjer Inst I	
Danske Invest Norske Aksjer Inst II	
DNB Norge	
DNB Norge III	
DNB Norge IV	
DNB Norge Selektiv	
DNB Norge Selektiv II	
DNB Norge Selektiv III	
Eika Norge	
Handelsbanken Norge	
KLP AksjeNorge	
Nordea Avkastning	
Nordea Kapital	
Pluss Aksje	
Pluss Markedsverdi	
Storebrand Aksje Innland	
Storebrand Norge I	
Storebrand Verdi	

50 %

6 %

Tracking Error

Table 6.1: Summary of findings for identifying investment strategies. Source: Own creation

Group	# of funds	Active Share	Average annual net alpha	Average gamma	TER
Concentrated Stock Pickers	11	68.48%	-0,63 %	0.02	1.85%
Diversified Stock Pickers	2	56.99%	-0.28%	-0.05	1.00%
Factor Bets	2	37.85%	-1.16%	-0.72	1.75%
Closet Indexing Funds	23	34.61%	0,01 %	0.41	1.24%

Based on the two-dimensional results presented in Figure 6.1, and the summary of findings presented in Table 6.1, there are several startling observations. First, I identify as many as 23 closet-indexing funds. That is, as many as 60% of the actively managed equity mutual funds in Norway are in fact highly passive, and have no overall investment strategy at all. Hence, an investor looking to invest in a Norwegian actively managed equity mutual fund is facing a risk of actually investing in the exact opposite investment product more than half of the time. Furthermore, looking at the average TER of the closet-index funds, it is evident that the investor would severely overpay for the product. A typical index-trailing fund, more commonly referred to as a passively managed fund, has a TER around 0.10 – 0.20%. It is lower than actively managed funds, because replicating a benchmark portfolio is a simple task often done by computers. Hence, there is no fund managers or analytics involved that require management fees and bonuses. However, the average TER among the 23 closet-index funds illustrates that the investor would overpay in excess of 1 % each year. That is, the investor is facing a risk of receiving the opposite product of what he is requesting and severely overpaying for it 60% of the times. In other words, he will only receive the product he is paying for 40% of the times.

Second, only 11 funds are identified as “concentrated stock pickers”, and are thus highly active. That is, they are engaging in both stock picking and market timing, and thus maintain a portfolio that is sufficiently differentiated from the benchmark portfolio while at the same time take on a sufficient level of risk. These are the funds that truly have the rights to charge fees as if they were actively managed. The average TER among the concentrated stock pickers is 1.85%, which is fair given their average active share of 68.48%. Thus, only 29% of the actively managed equity mutual funds in Norway are in fact actively managed. This must be deemed a devastating result from the industry’s point of view, and proves that the Norwegian media and government’s recent critique is just.

Unfortunately, I am only able to identify two funds within each of the last two groups, “diversified stock pickers” and “factor bets”. Thus, there are too few funds, and the potential of an outlier heavily biasing the results are too high, to provide any in-depth analysis of these funds. On the other hand, the fact that I am able to identify some funds as “factor bets”, indicate that it is important to measure activity across different dimensions in order to obtain the correct picture. The two funds, *Odin Norge C* and *Storebrand*

Norge, would be classified as highly passive if one only took active share into account. When the tracking error is introduced, they score above the threshold of 6%. Remembering that tracking error is a proxy for market timing (see section 2.1.3), the funds classified as “factor bets” is attempting to time macro movements which is an active strategy. The low active share would thus underestimate the activity level within the “factor bets” funds. If there were regulatory measures to be put on activity levels, indirectly concerning the Norwegian governments critique of active fund management, these findings emphasizes that it is important to measure the activity across different dimensions before one judge a fund as passively managed. These findings are in line with Norstein & Varran’s (2015) observations on the relationship between active share and tracking error.

Table 6.1 illustrates that the average net alpha of the concentrated stock pickers is -0.63%. That is, an investor would receive 0.63% more on his investments annually by investing in the benchmark index. With an average net alpha of -0.63% and a TER of 1.85%, it is evident that the fees erase all potential outperformance, and the investors are receiving underperformance at a higher price instead. Comparing the average net alpha from the concentrated stock pickers to the closet-indexing fund, we see that the closet-indexing funds are actually performing better. An average net alpha of 0.01% indicates neutral performance, and is actually the highest among the four groups in Figure 6.1. This finding might indicate that a more active strategy will not provide additional outperformance after deduction of fees. In the following sub-section, the relationship between activity levels and net alpha will be investigated further.

6.2 Activity levels vs. performance & micro forecasting abilities

It would be in the interest of any investor looking to invest in Norwegian equity mutual fund to know whether the more active funds perform better than the more passive fund. The more active funds take on higher risk in their portfolio, and thus have the potential of receiving higher returns. However, increased risk also implies an increased downside potential. Table 6.2 below presents the ten most active funds and the ten least active funds in the data sample along with their respective net alphas. As we know from section 5, the net alpha illustrates the actual return the investors receive on their investments relative to what they would receive if they invested in the passive benchmark index.

Table 6.2: Activity levels vs. net alpha. Source: Own creation

Ranking	Fund	Active Share	Net Alpha	Significant alpha
1	DNB SMB	91,77 %	-6,94 %	No
2	Storebrand Vekst	78,61 %	-1,75 %	No
3	Danske Invest Norge Vekst	76,70 %	-1,23 %	No
4	Pareto Investment Fund A	70,61 %	2,35 %	No
5	Holberg Norge	70,36 %	-5,03 %	Yes
6	Pareto Aksje Norge A	67,97 %	-1,24 %	No
7	Forte Norge	65,66 %	-2,77 %	No
8	Nordea Norge Pluss	61,45 %	-0,23 %	No
9	Nordea Norge Verdi	59,95 %	1,80 %	No
10	Fondsfinans Norge	59,20 %	-1,51 %	No
Average Net Alpha			**-1,66 %**	
Ranking	**Fund**	**Active Share**	**Net Alpha**	**Significant alpha**
29	Danske Invest Norge II	31,46 %	2,22 %	No
30	Danske Invest Norge I	31,22 %	1,47 %	No
31	Danske Invest Inst. I	30,95 %	2,96 %	Yes
32	DNB Norge IV	30,62 %	-0,48 %	No
33	DNB Norge III	30,61 %	-0,73 %	No
34	DNB Norge	30,61 %	-1,51 %	No
35	KLP AksjeNorge	28,69 %	-0,97 %	No
36	Storebrand Norge I	25,76 %	-1,38 %	No
37	Pluss Markedsverdi	25,42 %	1,57 %	No
38	Storebrand Aksje Innland	19,62 %	-1,26 %	No
Average Net Alpha			**0,19 %**	

Looking at the average net alphas of the top ten and bottom ten funds presented above, I obtain some startling results. According to my findings, the most active funds in my sample actually underperforms relative to the benchmark by 1.66% on average each year. That is, an investor investing in the most active funds receives a return on his investment that is 1.66% lower per year than if he invested in the passive benchmark. Remembering that investing in a passively managed product is substantially cheaper, actively managed fund could potentially lead to substantial losses over time. For instance, an investor investing 1 000 000 NOK in year 0 would miss out on 16 600 NOK in the first year if the market return was 0%. Due to a continuing reduction of the initial investment, the invest would miss 154 133 NOK[36] in a ten year time horizon by simply investing in a product that is supposed to yield abnormal return before inflation is even considered.

Looking at the least active funds, on the other hand, we see that the average fund is actually outperforming the passive benchmark by 0.19% on average each year. In other words, an investor would be better off by investing in the least active funds, and would receive a return that is 1.85% higher on average each year by

[36] If the market return was 0% on average in the ten year time horizon.

doing so. Using the same example as above, the investor would receive 173 296 NOK more on average on his initial investment by investing in the least active funds in ten years instead of the most active funds.

So far, there seems to be an inverse relationship between activity levels and performance. However, I have only been looking at aggregate levels by putting the average net alphas under scrutiny. Looking past the average numbers does not improve the findings: there are only two of the top ten funds that are able to obtain a positive net alpha, namely *Pareto Investment Fund A* and *Nordea Norge Verdi*, with a net alpha of 2.35% and 1.80% respectively. At the same time, the most active fund in the sample, *DNB SMB*, obtains an annual net alpha of -6.94%, which is surprisingly poor. Similarly, the fifth most active fund in the sample, *Holberg Norge*, obtains an annual net alpha of -5.03%. The same investor as above, with his initial investment of 1 000 000 NOK, would in a ten year period lose 512 866 NOK and 403 151 NOK respectively if he invested in these two funds instead of the benchmark index. This example emphasizes that an investor blindly investing in a Norwegian actively managed equity mutual fund face the risk of receiving substantial inferior returns.

Conversely, Table 6.2 illustrates that there are five funds, among the ten least active funds, that obtain a positive net alpha. Amongst them we find *Danske Invest Institusjon I,* which was identified in section 5.3.2.1 as the fund with the highest net alpha coefficient among the funds in my sample. In practice, they are only differentiating 30.95% of their portfolio from the benchmark, but the differentiated securities are delivering a correspondingly high outperformance to generate a positive net alpha. In other words, the underpriced securities they do identify and invest in, regardless of the low volume, is outperforming the benchmark largely. With this in mind, it is not surprising that I find evidence of superior micro forecasting within *Danske Invest Institusjon I*. If we take the findings from the two previous paragraphs into account, the inverse relationship between activity levels and performance seems to hold water when analyzing the funds at an individual level as well.

As the most active funds are the ones diversifying their portfolios the most, they continuously have to identify underpriced securities in order to outperform the benchmark over time. By investigating if there are evidence of superior micro forecasting abilities among the most active funds or least active funds, I am able to analyze the link between activity levels and fund manager abilities. As mentioned, *Danske Invest Institusjon I* is identified with superior micro forecasting abilities. That is, I am able to find evidence for superior abilities among the least active funds in the sample. Among the most active funds, on the other hand, *Holberg Norge* is identified with *inferior* micro forecasting skills. In other words, I am able to find evidence of superior micro forecasting abilities among the least active funds, but not among the most active funds. Hence, the claim of an inverse relationship between activity levels and performance is strengthened.

6.3 Activity levels vs. macro forecasting abilities

Following the findings of an inverse relationship between activity levels and performance/micro forecasting abilities, I extend the analysis to include the relationship between activity levels and macro forecasting abilities. Table 6.3 presents the ten most active funds and the ten least active funds, along with their respective gamma coefficients.

Table 6.3: Activity levels vs. gamma coefficients. Source: Own creation

Ranking	Fund	Active Share	Gamma	Significant gamma
1	DNB SMB	91,77 %	1,24	No
2	Storebrand Vekst	78,61 %	0,21	No
3	Danske Invest Norge Vekst	76,70 %	-0,42	No
4	Pareto Investment Fund A	70,61 %	-0,63	Yes
5	Holberg Norge	70,36 %	-0,56	No
6	Pareto Aksje Norge A	67,97 %	-0,81	Yes
7	Forte Norge	65,66 %	2,12	Yes
8	Nordea Norge Pluss	61,45 %	0,51	No
9	Nordea Norge Verdi	59,95 %	0,06	No
10	Fondsfinans Norge	59,20 %	-0,07	No
Average gamma			**0,17**	
Ranking	**Fund**	**Active Share**	**Gamma**	**Significant gamma**
29	Danske Invest Norge II	31,46 %	0,27	Yes
30	Danske Invest Norge I	31,22 %	0,23	Yes
31	Danske Invest Inst. I	30,95 %	0,26	Yes
32	DNB Norge IV	30,62 %	0,63	No
33	DNB Norge III	30,61 %	0,64	No
34	DNB Norge	30,61 %	0,63	No
35	KLP AksjeNorge	28,69 %	-0,35	No
36	Storebrand Norge I	25,76 %	0,20	No
37	Pluss Markedsverdi	25,42 %	0,26	Yes
38	Storebrand Aksje Innland	19,62 %	0,60	No
Average gamma			**0,337**	

Looking at the ten most active funds, it is evident that only three of the funds obtain a significant gamma coefficient. Out of the three, *Pareto Investment Fund A* and *Pareto Aksje Norge A* obtain a significantly negative gamma coefficient, which implies that their fund managers are able to predict the market, but constantly in the wrong direction. Only *Forte Norge* obtain a significant positive gamma, and thus show evidence of superior macro forecasting abilities among the most active funds in the sample.

On the other hand, I am able to identify four funds among the least active funds in my sample with a significant gamma coefficient. *Danske Invest Norge II, Danske Invest Norge I, Danske Invest Institusjon* I and

Pluss Markedsverdi all obtain a significant positive gamma. These findings imply that the less active funds indeed tend to be better macro forecasters than the more active funds. Thus, the inverse relationship between activity levels and abilities identified in the previous section is maintained when comparing activity levels and the presence of macro forecasting abilities. All evidence point to the fact that the funds that differentiate their portfolios the least from the benchmark portfolio are performing the best both in terms of performance and in terms of displaying superior abilities. In other words, the more active the funds get, the more difficult it seems become to significantly outperform a passive benchmark. This is in direct contrast to what the industry itself portrays as the biggest selling point of active fund management: increased potential of abnormal returns through stock picking and market timing.

At this point, it is natural to wonder why these results present themselves. As mentioned in section 5.4, macro forecasters are trying to capture more of the market upswings and less of the downturns by actively altering their portfolios between high and low beta stocks based on the prevailing market conditions. . In practice, this means increasing the overall risk in the portfolio when the market outlook is positive, and reduces the risk in negative outlooks. However, at some level, it seems like the benefits of altering the portfolio between high and low beta stocks is outweighed by the major differences in portfolio holdings between the funds and the benchmark.

In order to obtain a high active share, simply reducing or increasing the holdings of the exact same securities listed in the benchmark is not enough; the funds need to invest in securities that are not included in the benchmark at all. However, in small financial markets, such as the Norwegian, there are a limited number of high liquidity securities in which the funds can invest. On 31.12.2015, there was 207 securities listed on OSE[37]. When the OSEFX consists of 58 stocks, the number of remaining high liquidity funds is substantially reduced, making it challenging to identify attractive high beta and low beta stocks with sufficient liquidity. By solely focusing on differentiating the portfolio sufficiently from the benchmark index in order to maximize the active share, the funds might have to sacrifice performance, and micro and macro forecasting. Hence, in terms of maximizing performance and abilities, there might be an optimal level of activity within the funds that is heavily affected by the size of the financial market the funds are operating within. Identifying this optimal activity level within the Norwegian actively managed equity mutual fund would be interesting. However, as it falls outside of the scope of this study, it will not be touched upon.

So far, the findings has been dismal from the actively managed fund industry's point of view, and it appears that the Norwegian government and media's critique of the industry is justified. Both in terms of

[37] http://www.oslobors.no/Oslo-Boers/Statistikk/Fakta-og-noekkeltall/2015-Fakta-og-noekkeltall-desember-2015 - downloaded 05.10.2016

performance and abilities the least active funds achieve better results. In theory, the least active funds are supposed to be cheaper than the most active funds due to lower risk and lower management fees because of the reduced activity. However, are they really cheaper? Are investors overpaying for the product they receive? In the following section the individual funds' activity levels and TER will be analyzed together in order to elucidate this question.

6.4 Activity levels vs. TER

As mentioned previously in this study, the more active funds tend to be more expensive because actively seeking out underpriced stocks and constantly rebalancing portfolios is a resource-intensive task. One of the most important selection criteria applied when determining the data sample for this study (ref. section 3.1), addressed the issue of only including self-proclaimed actively managed funds. Hence, I ended up with 38 funds, all of which charge their investors as if they are actively managed. However, as identified in section 5.1, only 14 funds obtain an active share above the threshold of 50%. That is, only 14 funds can justify a high TER based on high activity levels. Furthermore, the findings from section 5.1 might indicate that the majority of the funds in the sample is overcharging their investors for the product they deliver. Table 6.4 below, presents the relationship between activity levels and costs for the top 10 most active and top 10 least active funds.

Table 6.4: Activity levels vs. TER. Source: Own creation

Ranking	Fund	Active Share	TER
1	DNB SMB	91,77 %	2,01 %
2	Storebrand Vekst	78,61 %	2,00 %
3	Danske Invest Norge Vekst	76,70 %	1,75 %
4	Pareto Investment Fund A	70,61 %	1,80 %
5	Holberg Norge	70,36 %	1,50 %
6	Pareto Aksje Norge A	67,97 %	2,50 %
7	Forte Norge	65,66 %	2,00 %
8	Nordea Norge Pluss	61,45 %	1,00 %
9	Nordea Norge Verdi	59,95 %	1,50 %
10	Fondsfinans Norge	59,20 %	1,00 %
Average TER			**1,71 %**
Ranking	**Fund**	**Active Share**	**TER**
29	Danske Invest Norge II	31,46 %	1,25 %
30	Danske Invest Norge I	31,22 %	2,00 %
31	Danske Invest Inst. I	30,95 %	0,90 %
32	DNB Norge IV	30,62 %	0,75 %
33	DNB Norge III	30,61 %	1,09 %
34	DNB Norge	30,61 %	1,80 %
35	KLP AksjeNorge	28,69 %	0,75 %
36	Storebrand Norge I	25,76 %	0,28 %
37	Pluss Markedsverdi	25,42 %	0,90 %
38	Storebrand Aksje Innland	19,62 %	0,60 %
Average TER			**1,03 %**

Looking at the average TERs it is clear that the most active funds are indeed the most expensive on average. The ten most active funds obtain an average TER of 1.71%, while the ten least active funds obtain an average TER of 1.03%. The fact that the most active funds are the most expensive is in line with theory, and as one would expect. However, funds with an active share below 50% are by definition passively managed, and should be priced accordingly. Given the fact that passively managed funds tend to have a TER in the range from 0.10% to 0.20%, an average TER of the ten least active funds of 1.03% is surprisingly high. In practice, these findings imply that investors might overpay in extent of 0.80% each year for a passively managed product.

Looking past the average numbers, and analyzing the data on an individual fund level, the results become even more startling. Even though, the ten least active funds are cheaper than the ten most active funds on average, certain funds are heavily overpriced. For instance, *Danske Invest Norge I* is the ninth least active funds with an active share of 31.22%, but have the fourth highest TER of 2.00% (see Appendix 2). Similarly, DNB Norge is the fifth least active fund with an active share of 30.61%, but charges its investors 1.80% annually, which is the 12th highest TER. Conversely, looking at the ten most active funds, *Nordea Norge Pluss* and *Fondsfinans Norge* are the eight and tenth most active funds, but only charges their investors

1.00% annually, which represents a TER below the bottom ten average. Hence, there appear to be no real coherence between activity levels and costs in the Norwegian actively managed equity mutual fund market. An unknowing investor does face a certain risk of severely overpaying for the product he is receiving. On the other hand, the results on *Nordea Norge Pluss* and *Fondsfinans Norge* indicate that there is a slight chance of getting an actively managed product at a price below the anticipated price range.

Based on the findings from this study, only one fund seem to be priced somewhat fair given its activity levels, namely *Storebrand Norge I.* This finding corresponds to only 2.6% of the equity mutual funds in the Norwegian market being fairly priced, given that my data sample is representative for the market as a whole. *Storebrand Norge I* is classified as a passively managed fund due to its active share of only 25.76%, but has a TER of 0.28%, which is close to the before mentioned standard for a passively managed fund. However, the fact that I am only able to identify one fund as fairly is a dismal finding, and further emphasizes the point of irrational fund pricing in the Norwegian market.

7.0 Conclusion

This study covers a fraction of the Norwegian fund market, by analyzing the performance and activity levels within 38 self-proclaimed actively managed equity mutual funds. The funds in the sample are primarily investing in Norwegian securities listed on OSE. In terms of performance, the funds have been analyzed in the period from 1 January 2006 to 31 December 2015.

According to theory, actively managed funds are expected to be more expensive to investors than the passively managed alternative. This is because actively managed funds are consistently gathering information and performing fundamental and technical analyses on the financial market in order to identify mispriced securities, which is a highly resource intensive task. However, the Norwegian government and media have recently criticized the domestic equity mutual funds for not being active enough, and thus severely overcharging for the product they deliver. The results from my tests indicate that the Norwegian government and media's criticism is just.

First, by combining Cremers & Petajisto's active share measure with the traditional tracking error volatility, I identify a substantial overload of closet indexing funds in the Norwegian equity mutual funds. In fact, out of 38 self-proclaimed actively managed equity mutual funds, as many as 23 are classified as closet indexing. Hence, approximately 60% of the available actively managed equity mutual funds in the Norwegian market are in fact highly passive. These findings imply that there is a high probability for an unknowing investor to pay for active management, but receiving the exact opposite product in reality.

Second, I am not able to find evidence for the more active funds being better performers on average. By applying a Jensen's alpha regression, both in a static and time-varying beta scenario, I am able to pinpoint the funds' annual performance during the last ten years. However, there are no evidence of superior performance among the most active funds. In fact, the least active funds tend to perform better than the most active funds in my sample, which is a dismal finding for the Norwegian actively managed equity mutual fund industry. The activity levels of actively managed Norwegian equity mutual funds does *not* coincide with performance. Furthermore, the Jensen regression reveals that the most active funds are *not* the best micro forecasters, which is surprising taking into account that their strategy is in fact to identify underpriced securities. Opposite of what one would expect, I am able to identify an inverse relationship between activity and micro forecasting skills; the least active funds tend to be the best micro forecasters. Hence, this study finds the Norwegian government and media's argument of the actively managed funds not delivering performance at a satisfactory level correct.

Extending the tests to include macro forecasting abilities by including the Treynor & Mazuy market timing model, I find evidence for the same pattern. The least active funds are better at anticipating market movements than the most active funds. Hence, the inverse relationship between activity levels and abilities holds for macro forecasting abilities, as well as micro forecasting abilities. That is, an investor would benefit more from investing in the least active funds, which is a devastating finding for the actively managed equity mutual fund industry.

Finally, my findings imply that there is not a rational relationship between activity levels and costs in the Norwegian equity mutual fund market. Even though the least active funds are cheaper on average, there are several evidences of individual closet indexing funds charging their investors as if they were highly active. In addition, a few of the most active funds in the sample charge fees at a level that should imply a lower activity level. Hence, the activity levels does not coincide with the costs and investors are constantly facing the risk of severely overpaying for the product they receive.

The findings in this study fully supports the Norwegian government and media's criticism of the actively managed fund industry. In every aspect and test applied, the active funds fall short of expectations. The funds are less active than one should expect, they perform worse than one should expect, and the investors are overpaying for the product they receive. Taking into account that the least active funds tend to perform better on average, and clearly benefits the investors more, one could start to question the entire existence of the industry.

8.0 Suggested future research

My suggestion for future research stems from the findings of the least active funds performing better on average than the most active funds. Hence, it appears that higher activity levels does not automatically imply better performance. Following these findings, it would be interesting to extend my research and try to identify the optimal activity levels within actively managed Norwegian equity mutual funds.

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Danske Invest’s weekly market report, week 33/2016, *Oslo*

10.0 Appendices

10.1 Appendix 1: OSEFX Constituents (31.12.2015)

OSEFX Consituents 31.12.15

Investment	Weights
Statoil	9,00 %
Telenor	9,00 %
DNB ASA	9,00 %
Yara International ASA	9,00 %
Orkla	4,50 %
Norsk Hydro ASA	4,50 %
Royal Carribbean Cruises (NOK)	4,50 %
Marine Harvest	4,50 %
Gjenside Forsikring ASA	4,00 %
Schibsted ser. B	2,36 %
Schibsted ser. A	2,14 %
Subsea 7 S.A (NOK)	2,69 %
TGS-NOPEC Geophysical Company	2,53 %
Storebrand	2,11 %
Veidekke	1,78 %
Bakkafrost	1,68 %
Tomra Systems	1,61 %
Seadrill	1,49 %
XXL	1,42 %
Norwegian Air Shuttle ASA	1,35 %
Petroleum Geo-Service	1,29 %
Kongsberg Gruppen	1,24 %
SalMar	1,08 %
Opera Software	1,03 %
Atea	1,01 %
Entra	1,00 %
Nordic Semiconductor ASA	0,99 %
Det Norske Oljeselskap	0,91 %
AF Gruppen	0,88 %
DNO	0,85 %
Aker Solutions	0,80 %
Prosafe SE	0,78 %
Olav Thon Eiendomsselskap	0,69 %
BW LPG	0,67 %
Aker	0,65 %
Europris	0,63 %
IDEX	0,63 %
REC Silicon	0,52 %
Ekornes	0,43 %
Avance Gas Holding	0,41 %
ABG Sundal Collier Holding	0,41 %
Stolt-Nielsen	0,38 %
Wilh. Wilhelmsen ASA	0,37 %
Scatec Solar	0,33 %
Wilh. Wilhelmsen Holding ser. A	0,33 %
Multiconsult	0,31 %
Kongsberg Automotive	0,30 %
Thin Film Electronics	0,30 %
Norwegian Property	0,29 %
Frontline	0,27 %
Wilh. Wilhelmsen Holding ser. B	0,23 %
Golden Ocean Group	0,20 %
American Shipping Company	0,18 %
Photocure	0,12 %
Weifa	0,11 %
Biotec Pharmacon	0,08 %
Q-Free	0,07 %
Nordic Nanovector	0,07 %

10.2 Appendix 2: Active Share w/ Tracking Error, AUM and TER

Ranking	Fund	Active Share	Tracking Error	AUM (in 1000 NOK)	Ranking by AUM	TER
15	Alfred Berg Aktiv	47,00 %	5,18 %	543 891,00	20	1,50 %
11	Alfred Berg Gambak	56,35 %	7,58 %	1 797 977,00	9	1,80 %
19	Carnegie Aksje Norge	42,05 %	3,24 %	355 589,00	26	1,20 %
30	Danske Invest Norge I	31,22 %	4,58 %	28 786,00	37	2,00 %
29	Danske Invest Norge II	31,46 %	4,67 %	352 584,00	27	1,25 %
3	Danske Invest Norge Vekst	76,70 %	10,97 %	22 453,00	38	1,75 %
31	Danske Invest Norske Aksjer Inst. I	30,95 %	4,43 %	472 762,00	23	0,90 %
28	Danske Invest Norske Aksjer Inst. II	31,61 %	4,49 %	949 817,00	16	0,90 %
12	Delphi Norge	56,05 %	6,58 %	760 445,00	17	2,00 %
34	DNB Norge	30,61 %	3,76 %	7 070 638,00	1	1,80 %
33	DNB Norge III	30,61 %	3,74 %	118 923,00	33	1,09 %
32	DNB Norge IV	30,62 %	3,72 %	319 307,00	28	0,75 %
23	DNB Norge Selektiv	41,02 %	4,76 %	531 064,00	21	2,01 %
20	DNB Norge Selektiv II	41,52 %	4,81 %	174 153,00	31	1,01 %
22	DNB Norge Selektiv III	41,08 %	4,77 %	1 335 379,00	10	0,80 %
1	DNB SMB	91,77 %	12,25 %	645 286,00	18	2,01 %
25	Eika Norge	36,87 %	5,73 %	1 262 070,00	11	2,00 %
10	Fondsfinans Norge	59,20 %	6,70 %	1 124 845,00	14	1,00 %
7	Forte Norge	65,66 %	7,48 %	32 103,00	36	2,00 %
21	Handelsbanken Norge	41,24 %	5,68 %	3 145 223,00	7	2,00 %
5	Holberg Norge	70,36 %	8,42 %	508 750,00	22	1,50 %
35	KLP AksjeNorge	28,69 %	4,82 %	4 983 431,00	2	0,75 %
13	Landkreditt Norge	52,70 %	7,66 %	52 119,00	35	1,75 %
17	Nordea Avkastning	45,62 %	2,63 %	2 784 652,00	8	1,50 %
24	Nordea Kapital	39,29 %	2,73 %	3 467 464,00	5	1,00 %
8	Nordea Norge Pluss	61,45 %	3,85 %	277 826,00	29	1,00 %
9	Nordea Norge Verdi	59,95 %	7,99 %	3 367 515,00	6	1,50 %
18	Odin Norge C	43,99 %	10,00 %	4 777 947,00	3	2,00 %
6	Pareto Aksje Norge - Andelsklasse A	67,97 %	9,45 %	1 149 583,00	13	2,50 %
4	Pareto Investment Fund A	70,61 %	7,56 %	441 983,00	24	1,80 %
26	Pluss Aksje	34,69 %	5,00 %	118 281,00	34	1,20 %
37	Pluss Markedsverdi	25,42 %	3,29 %	134 733,00	32	0,90 %
38	Storebrand Aksje Innland	19,62 %	3,50 %	1 197 488,00	12	0,60 %
27	Storebrand Norge	31,71 %	15,45 %	249 197,00	30	1,50 %
36	Storebrand Norge I	25,76 %	3,99 %	4 506 200,00	4	0,28 %
14	Storebrand Optima Norge	52,53 %	5,80 %	422 574,00	25	1,00 %
2	Storebrand Vekst	78,61 %	11,42 %	624 036,00	19	2,00 %
16	Storebrand Verdi	46,91 %	5,39 %	987 826,00	15	2,00 %

10.3 Appendix 3: Jensen's Alpha in a stationary risk level scenario

**** p < 0.01** *** p < 0.05**

Fund name	Net Returns Yearly α	t-stat	β	Obs.	Gross Returns Yearly α	t-stat	R^2 adj.
Alfred Berg Aktiv	0.0168	(1.07)	0.94154	120	**0.0318***	**(2.01)**	0.9543
Alfred Berg Gambak	0.0294	(1.34)	0.91167	120	**0.0473***	**(2.13)**	0.9106
Carnegie Aksje Norge	0.0153	(1.42)	0.95732	120	**0.0277****	**(2.55)**	0.9802
Danske Invest Inst. I	**0.0383***	**(3.02)**	0.91189	120	**0.0481****	**(3.77)**	0.9680
Danske Invest Inst. II	**0.0377****	**(2.97)**	0.91004	120	**0.0473****	**(3.84)**	0.9647
Danske Invest Norge I	**0.0255***	**(2.01)**	0.90527	120	**0.0466****	**(3.66)**	0.9667
Danske Invest Norge II	**0.0342****	**(2.66)**	0.89666	120	**0.0474****	**(3.68)**	0.9654
Danske Invest Norge Vekst	-0.0123	(-0.64)	0.85583	120	0.0054	(0.28)	0.9171
Delphi Fondene Norge	0.0119	(0.51)	0.93391	63	0.0324	(1.38)	0.8578
DNB Norge	-0,0151	(-0.90)	0.94264	60	0.0036	(0.22)	0.9170
DNB Norge III	-0,0073	(-0.44)	0.94212	60	0.0041	(0.25)	0.9166
DNB Norge IV	-0,0048	(-0.28)	0.94454	60	0.0031	(0.18)	0.9167
DNB Norge Selektiv I	-0,0177	(-0.83)	0.96648	60	0.0038	(0.18)	0.8788
DNB Norge Selektiv II	-0,0742	(-0.36)	0.96512	60	0.0032	(0.15)	0.8777
DNB Norge Selektiv III	-0,0057	(-0.26)	0.96839	60	0.0029	(0.14)	0.8780
DNB SMB	-0,0694	(-1.50)	1.07035	60	-0,0510	(-1.09)	0.6383
Eika Norge	0,0043	(0.23)	0.91895	120	0.0248	(1.29)	0.9270
Fondsfinans Norge	0,0346	(1.72)	0.90212	120	**0.0451***	**(2.23)**	0.9246
Forte Norge	-0,0277	(-0.77)	0.93330	56	-0.0062	(-0.17)	0.7581
Handelsbanken Norge	0,0304	(1.80)	0.9895	120	**0.0503****	**(2.95)**	0.9533
Holberg Norge	-0,0251	(-1.16)	0.76700	120	-0.0113	(-0.53)	0.8824
KLP Aksje Norge	0,0094	(0.54)	0.93057	120	0.0169	(0.95)	0.9521
Landkreditt Norge	0,0025	(0.11)	0.84667	114	0.0210	(0.93)	0.8973
Nordea Avkastning	0,0025	(0.32)	0.95913	120	**0.0179***	**(2.24)**	0.9884
Nordea Kapital	0,0135	(1.64)	0.94871	120	**0.0240****	**(2.89)**	0.9875
Nordea Norge Pluss	-0,0023	(-0.13)	0.98952	56	0.0083	(0.46)	0.9320
Nordea Norge Verdi	0,018	(0.93)	0.75561	120	0.0326	(1.67)	0.9023
Odin Norge C	-0,0264	(-0.99)	0.73749	107	-0,0079	(-0.30)	0.8438
Pareto Aksje Norge A	-0,0124	(-0.51)	0.75098	120	0,0106	(0.43)	0.8506
Pareto Investment Fund A	0,0235	(1.20)	0.94362	120	**0,0418***	**(2.10)**	0.9327
Pluss Aksje	0,0267	(1.93)	0.83734	120	**0,0393****	**(2.81)**	0.9594
Pluss Markedsverdi	**0,0229***	**(2.39)**	0.91458	120	**0,0323****	**(3.35)**	0.9821
Storebrand Aksje Innland	-0,0122	(-0.84)	0.92806	57	-0,0060	(-0.42)	0.9470
Storebrand Norge I	-0,0138	(-0.82)	0.92731	57	-0,0110	(-0.65)	0.9285
Storebrand Norge	0,0032	(0.22)	0.95101	63	0,019	(1.27)	0.9333
Storebrand Optima Norge	-0,0034	(-0.11)	0.93475	57	0,0067	(0.22)	0.7792
Storebrand Vekst	0,0347	(0.74)	0.82637	63	0,0533	(1.14)	0.5515
Storebrand Verdi	-0,0149	(-0.93)	0.89639	63	0,0046	(0.28)	0.9198

10.4 Appendix 4: Jensen's alpha in a time-varying risk scenario

** $p < 0.01$ * $p < 0.05$

	Net Returns				Gross Returns			
Fund name	Yearly α	t-stat	β	Obs.	Yearly α	t-stat	R^2 adj.	F-Value
Alfred Berg Aktiv	0.0102	(0.62)	0.96483	120	0.0251	(1.52)	0.9548	2.551
Alfred Berg Gambak	0.0354	(1.51)	0.89109	120	**0.0535***	**(2.26)**	0.9105	1.036
Carnegie Aksje Norge	0.0096	(1.00)	0.97684	120	**0.0219***	**(2.26)**	0.9806	4.096
Danske Invest Inst. I	**0.0296***	**(2.21)**	0.90642	120	**0.0391****	**(2.91)**	0.9694	**6.723***
Danske Invest Inst. II	**0.0270****	**(3.07)**	0.90812	109	**0.0381****	**(2.88)**	0.9685	**6.723***
Danske Invest Norge I	0.0147	(1.14)	0.94254	120	**0.0355****	**(2.73)**	0.9690	**10.000***
Danske Invest Norge II	0.0222	(1.70)	0.93803	120	**0.0352****	**(2.69)**	0.9683	**12.500***
Danske Invest Norge Vekst	-0.0228	(-1.17)	0.89447	120	-0.0053	(-0.27)	0.9193	4 068
Delphi Fondene Norge	0.0099	(0.42)	0.95237	63	0.0300	(1.27)	0.8568	0.833
DNB Norge	-0.0161	(-0.95)	0.94915	60	0.0025	(0.15)	0.9155	0.163
DNB Norge III	-0.0084	(-0.49)	0.94866	60	0.0030	(0.18)	0.9154	0.244
DNB Norge IV	-0.0059	(-0.34)	0.95109	60	0.0019	(0.12)	0.9154	0.242
DNB Norge Selektiv I	-0.0202	(-0.93)	0.98275	60	0.0011	(0.05)	0.8782	0.510
DNB Norge Selektiv II	-0.0103	(-0.47)	0.98150	60	0.0005	(0.02)	0.8772	0.505
DNB Norge Selektiv III	-0.0084	(-0.39)	0.98484	60	0.0001	(0.01)	0.8775	1.010
DNB SMB	-0.0781	(-1.75)	1.13420	60	-0.0608	(-1.39)	0.6500	3.108
Eika Norge	-0.0047	(-0.25)	0.95138	120	0.0155	(0.80)	0.9282	3.010
Fondsfinans Norge	-0.0151	(0.80)	0.97098	120	0.0252	(1.33)	0.9323	**14.599***
Forte Norge	-0.0358	(-1.02)	0.98120	56	-0.0153	(-0.43)	0.7683	3.555
Handelsbanken Norge	0.0336	(1.87)	0.97861	120	**0.0538****	**(2.96)**	0.9531	0.441
Holberg Norge	**-0.0503***	**(-2.61)**	0.86421	120	-0.0369	(-1.91)	0.9021	**25.080***
KLP Aksje Norge	-0.0097	(-0.77)	0.99921	120	-0.0025	(-0.19)	0.9597	**23.529***
Landkreditt Norge	-0.0154	(-0.73)	0.91187	114	0.0025	(0.12)	0.9046	**9.632***
Nordea Avkastning	-0.0029	(-0.35)	0.97817	120	0.0124	(1.53)	0.9889	**6.809***
Nordea Kapital	-0.0075	(0.90)	0.96988	120	**0.0177***	**(2.14)**	0.9882	**7.959***
Nordea Norge Pluss	-0.0062	(-0.36)	1.00853	56	0.0042	(0.24)	0.9338	2 569
Nordea Norge Verdi	0.0156	(0.83)	0.76406	120	0.0302	(1.59)	0.9017	0.000
Odin Norge C	-0.0398	(-1.46)	0.79429	107	-0.0215	(-0.79)	0.8487	4.609
Pareto Aksje Norge A	-0.0228	(-0.97)	0.79013	120	0.0000	(0.00)	0.8527	2.559
Pareto Investment Fund A	0.0188	(0.97)	0.96009	120	0.0370	(1.90)	0.9326	1.007
Pluss Aksje	0.0112	(1.02)	0.89024	120	**0.0234***	**(2.12)**	0.9652	**21.552***
Pluss Markedsverdi	0.0157	(1.72)	0.93896	120	**0.0250***	**(2.76)**	0.9831	**7.879***
Storebrand Aksje Innland	-0.0126	(-0.84)	0.93123	57	-0.0066	(-0.44)	0.9461	0.000
Storebrand Norge I	-0.0150	(-0.86)	0.93355	57	-0.0122	(-0.70)	0.9275	0.288
Storebrand Norge	0.0028	(0.18)	0.95652	63	0.0184	(1.24)	0.9323	0.092
Storebrand Optima Norge	-0.0055	(-0.18)	0.94587	57	0.0044	(0.15)	0.7760	0.259
Storebrand Vekst	0.0289	(0.63)	0.88005	63	0.0471	(1.02)	0.5539	1.419
Storebrand Verdi	-0.0131	(-0.82)	0.87662	63	0.0066	(0.41)	0.9203	1.391

10.5 Appendix 5: Treynor & Mazuy in a stationary risk scenario

** $p < 0.01$ * $p < 0.05$

Fund name	Net Returns α	t-stat	γ	t-stat	Obs.	R^2 adj.
Alfred Berg Aktiv	0.0155	(0.86)	0.02053	(0.15)	120	0.9539
Alfred Berg Gambak	0.0501	(1.95)	**-0.31694***	**(-2.28)**	120	0.9126
Carnegie Aksje Norge	0.0100	(0.88)	0.08975	(0.54)	120	0.9802
Danske Invest Inst. I	0.0211	(1.66)	**0.26352****	**(2.81)**	120	0.9698
Danske Invest Inst. II	0.0210	(1.66)	**0.26352****	**(2.81)**	120	0.9698
Danske Invest Norge I	0.0109	(0.86)	**0.22702***	**(2.01)**	120	0.9680
Danske Invest Norge II	0.0167	(1.29)	**0.27377***	**(2.62)**	120	0.9672
Danske Invest Norge Vekst	-0.0189	(-0.94)	0.10890	(0.55)	120	0.9167
Delphi Fondene Norge	0.0260	(0.94)	-0.62415	(-1.20)	63	0.8574
DNB Norge	-0.0278	(-1.35)	0.63420	(1.74)	60	0.9174
DNB Norge III	-0.0201	(-0.98)	0.63706	(1.74)	60	0.9170
DNB Norge IV	-0.0176	(-0.85)	0.63726	(1.74)	60	0.9170
DNB Norge Selektiv I	**-0.0506***	**(-2.17)**	**1.67134***	**(2.43)**	60	0.8884
DNB Norge Selektiv II	-0.0500	(-1.75)	**1.68048***	**(2.45)**	60	0.8875
DNB Norge Selektiv III	-0.0390	(-1.67)	**1.68039***	**(2.44)**	60	0.8877
DNB SMB	-0.0929	(-1.82)	1.24063	(0.81)	60	0.6356
Eika Norge	0.0010	(0.04)	0.05511	(0.28)	120	0.9264
Fondsfinans Norge	0.0083	(0.40)	0.41267	(1.64)	120	0.9290
Forte Norge	**-0.0712***	**(-2.08)**	**2.11689***	**(2.10)**	57	0.7711
Handelsbanken Norge	**0.0451***	**(2.33)**	**-0.22513***	**(-2.41)**	120	0.9541
Holberg Norge	**-0.0470***	**(-2.22)**	0.42822	(1.89)	120	0.8883
KLP Aksje Norge	-0.0106	(-0.63)	0.32224	(0.81)	120	0.9546
Landkreditt Norge	-0.0318	(-1.52)	**0.60455****	**(4.02)**	114	0.9083
Nordea Avkastning	-0.0065	(-0.83)	0.16087	(1.89)	120	0.9889
Nordea Kapital	0.0024	(0.24)	**0.18051***	**(2.10)**	120	0.9883
Nordea Norge Pluss	-0.0131	(-0.72)	0.50602	(0.79)	56	0.9318
Nordea Norge Verdi	0.0143	(0.70)	0.05869	(0.26)	120	0.9016
Odin Norge C	-0.0267	(-0.95)	0.00834	(0.19)	107	0.8423
Pareto Aksje Norge A	-0.0112	(-0.42)	-0.02039	(-0.08)	120	0.8493
Pareto Investment Fund A	0.0302	(1.43)	-0.10176	(-0.42)	120	0.9324
Pluss Aksje	-0.0047	(-0.36)	**0.49318****	**(2.87)**	120	0.9676
Pluss Markedsverdi	0.0061	(0.64)	**0.26316****	**(2.64)**	120	0.9840
Storebrand Aksje Innland	-0.0246	(-1.40)	0.60102	(1.51)	57	0.9478
Storebrand Norge I	-0.0181	(-0.84)	0.20424	(0.45)	57	0.9274
Storebrand Norge	0.0157	(0.99)	-0.55286	(-1.62)	63	0.9338
Storebrand Optima Norge	0.0098	(0.24)	-0.61218	(-0.73)	57	0.7765
Storebrand Vekst	0.0302	(0.55)	0.20558	(0.20)	63	0.5440
Storebrand Verdi	-0.0087	(-0.44)	-0.27799	(-0.80)	63	0.9189

10.6 Appendix 6: Treynor & Mazuy in a time-varying risk scenario

** $p < 0.01$ * $p < 0.05$

Fund name	Net Returns α	t-stat	γ	t-stat	β	Obs.	R^2 adj.	F-Value
Alfred Berg Aktiv	0.0234	(1.35)	**-0.39340***	**(-2.23)**	0.95788	120	0.9558	**6.316***
Alfred Berg Gambak	**0.0551***	**(2.17)**	**-0.56621****	**(-2.90)**	0.88151	120	0.9127	1 072
Carnegie Aksje Norge	0.0139	(1.14)	-0.12691	(-0.55)	0.97446	120	0.9806	3 780
Danske Invest Inst. I	0.0222	(1.77)	0.20963	(0.81)	0.94543	120	0.9696	0.855
Danske Invest Inst. II	0.0217	(1.74)	0.20047	(0.68)	0.94321	109	0.9707	0.855
Danske Invest Norge I	0.0162	(1.29)	-0.04241	(-0.18)	0.94179	120	0.9688	4 202
Danske Invest Norge II	0.0225	(1.79)	-0.00986	(-0.04)	0.93786	120	0.9681	4 167
Danske Invest Norge Vekst	-0.0092	(-0.46)	-0.41870	(-1.16)	0.88675	120	0.9204	**6.597***
Delphi Fondene Norge	0.0241	(0.88)	-0.64167	(-1.19)	0.94936	63	0.8565	0.422
DNB Norge	-0.0277	(-1.35)	0.60821	(1.80)	0.99357	60	0.9159	0.000
DNB Norge III	0.0201	(-0.98)	0.61084	(1.54)	0.95714	60	0.9156	0.083
DNB Norge IV	-0.0176	(-0.85)	0.61105	(1.54)	0.95957	60	0.9156	0.000
DNB Norge Selektiv I	**-0.0504***	**(-2.18)**	**1.61297***	**(2.22)**	1.00424	60	0.8866	0.000
DNB Norge Selektiv II	-0.0407	(-1.76)	**1.62145***	**(2.23)**	1.00311	60	0.8856	0.000
DNB Norge Selektiv III	-0.0388	(-1.67)	**1.62072***	**(2.23)**	1.00644	60	0.8859	0.000
DNB SMB	-0.0911	(-1.81)	0.72063	(0.62)	1.14459	60	0.6448	2 691
Eika Norge	0.0110	(0.56)	-0.46994	(-1.58)	0.94328	120	0.9296	**6.529***
Fondsfinans Norge	0.0175	(0.88)	-0.07199	(-0.28)	0.96965	120	0.9318	**5.861***
Forte Norge	**-0.0697***	**(-2.11)**	1.73991	(1.82)	1.00606	56	0.7750	1 995
Handelsbanken Norge	**0.0499***	**(2.59)**	**-0.46804****	**(-2.63)**	0.97034	120	0.9544	1 826
Holberg Norge	-0.0329	(-1.60)	-0.55837	(-1.61)	0.85417	120	0.9051	**22.408***
KLP Aksje Norge	0.0018	(0.10)	-0.34909	(-0.72)	0.99249	120	0.9605	**18.788***
Landkreditt Norge	-0.0346	(-1.45)	0.58420	(1.95)	0.92208	114	0.9075	0.000
Nordea Avkastning	-0.0061	(-0.70)	0.09753	(0.79)	0.97996	120	0.9889	0.638
Nordea Kapital	0.0031	(0.35)	0.12935	(1.04)	0.97225	120	0.9883	0.417
Nordea Norge Pluss	-0.0125	(-0.72)	0.31406	(0.52)	1.01327	56	0.9329	2 037
Nordea Norge Verdi	0.0152	(0.68)	0.01139	(0.03)	0.76426	120	0.9008	0.000
Odin Norge C	-0.0105	(-0.38)	**-0.89105***	**(-2.09)**	0.77952	107	0.8577	**12.688***
Pareto Aksje Norge A	0.0035	(0.14)	**-0.81281***	**(-2.03)**	0.77435	120	0.8596	**9.707***
Pareto Investment Fund A	**0.0406***	**(1.99)**	**-0.63058***	**(-2.87)**	0.94852	120	0.9355	**6.738***
Pluss Aksje	-0.0040	(-0.27)	0.45368	(1.47)	0.89896	120	0.9673	0.000
Pluss Markedsverdi	0.0055	(0.53)	0.30201	(1.59)	0.94461	120	0.9839	0.161
Storebrand Aksje Innland	-0.0247	(-1.41)	0.60509	(1.50)	0.94002	57	0.9468	0.000
Storebrand Norge I	-0.0180	(-0.85)	0.14873	(0.33)	0.93574	57	0.9262	0.192
Storebrand Norge	0.0152	(0.96)	-0.55786	(-1.62)	0.95380	63	0.9328	0.189
Storebrand Optima Norge	0.0101	(0.26)	-0.77675	(-0.91)	0.93420	57	0.7740	0.524
Storebrand Vekst	0.0257	(0.47)	0.14149	(0.15)	0.88069	63	0.8838	1 311
Storebrand Verdi	-0.0072	(-0.36)	-0.26593	(-0.86)	0.87523	63	0.9193	1 391